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Modeling destination choice in hurricane evacuation with an intervening opportunity model

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MODELING DESTINATION CHOICE IN HURRICANE EVACUATION WITH AN INTERVENING OPPORTUNITY MODEL

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ABSTRACT

In this study, a trip distribution model for hurricane evacuation using the intervening opportunity method was developed. Post Hurricane Floyd survey data was used for model calibration and comparison. To model the behavior that people tend to evacuate away from the path of the hurricane, a new concept of equal destination attractiveness was introduced and an extended intervening opportunity model was built on this basis and implemented in TransCAD. The gravity model, intervening opportunity model and its extended version were compared using several statistical measures. This study demonstrates that it is possible to use the intervening opportunity theory to model trip distribution in hurricane evacuation. The results also show that the gravity model performs slightly better than intervening opportunity model, while the extended intervening opportunity model performs the best among the three models.

Key words:

Intervening opportunity model, trip distribution, hurricane evacuation, TransCAD, Hurricane Floyd

CHAPTER 1. INTRODUCTION

1.1 Background

The power of hurricanes and the damage that they can bring to civilization have been known for centuries. The hazard of hurricanes comes in many forms: storm surge, high winds, tornadoes and flooding. According to the National Hurricane Center, in an average 3-year period, roughly five hurricanes strike the US coastline, killing approximately 50 to 100 people from Texas to Maine and bringing billions of dollars in property and other damage.

The forecasting of the track of a hurricane, though improving all the time, is a daunting task for scientists, since hurricanes are usually steered by weak and erratic winds. Nonetheless, the warnings issued by National Hurricane Center and local offices of emergency preparedness help greatly to reduce the damage and the fatalities caused by hurricanes.

In coastal areas before a hurricane strikes, a mandatory or voluntary evacuation is usually issued. People that live in flood zones or are vulnerable to the forces hurricanes can exert, need to evacuate to safer places. This process of evacuation involves moving a large population that may grow or change, onto a highly congested and possibly damaged road network, toward numerous destinations that may alter with time. Since the development of transportation facilities lags far behind the growth of coastal population, the managing of the evacuation process is an important issue; the fact that many lives are at stake only adds to the urgency of the subject. Therefore, a comprehensive and efficient evacuation plan must be developed to serve as the basis for evacuation management decisions.

1.2 Purpose of Study

The objectives of the study are:

- To model hurricane evacuation trip destination choices by the application of the intervening opportunity model calibrated using existing data from Hurricane Floyd.
- Compare the results of the intervening opportunity model with those of an independently estimated Gravity Model.
- Investigate a new extension of the intervening opportunity model, which accounts for the fact that people will evacuate to locations away from the path of a hurricane.

CHAPTER 2. LITERATURE REVIEW

2.1 Hurricanes

Hurricanes start as a tropical depression and progress to a tropical storm before becoming a hurricane. The stages of development of a hurricane can be described as follows. When a tropical depression has intensified to the point where its maximum sustained winds are between 35-64 knots (39-73 mph), it becomes a tropical storm, then the storm becomes more organized and begins to become more circular in shape -- resembling a hurricane. The main energy source is latent heat derived from condensed water vapor; therefore hurricanes are generated and continue to gather strength only within the confines of warm oceans. The various stages of tropical depressions and tropical storms are defined by Beaufort Wind Scale, which is shown in table 2-1.

Table 2-1. Beaufort wind scale

Scale	Wind Speed (Knots)	Stage
5	17-21	NA
6	22-27	Tropical Depression
7	28-33	Tropical Depression
8	34-40	Tropical Storm
9	41-47	Tropical Storm
10	48-55	Tropical Storm
11	56-63	Tropical Storm
12	>64	Cyclone, Hurricane, Typhoon, etc.

(Source: http://www.newmediastudio.org)

Out in the sea, classification is by maximum sustained wind speed experienced 10 m above sea level. Over land area, the intensity is judged by winds at about 1 km above the ground. Once the sustained winds in a tropical storm have reached at least 64 knots, it is referred to as a hurricane, cyclone or typhoon, depending on its location. Fig.2-1 shows their distribution around the world.

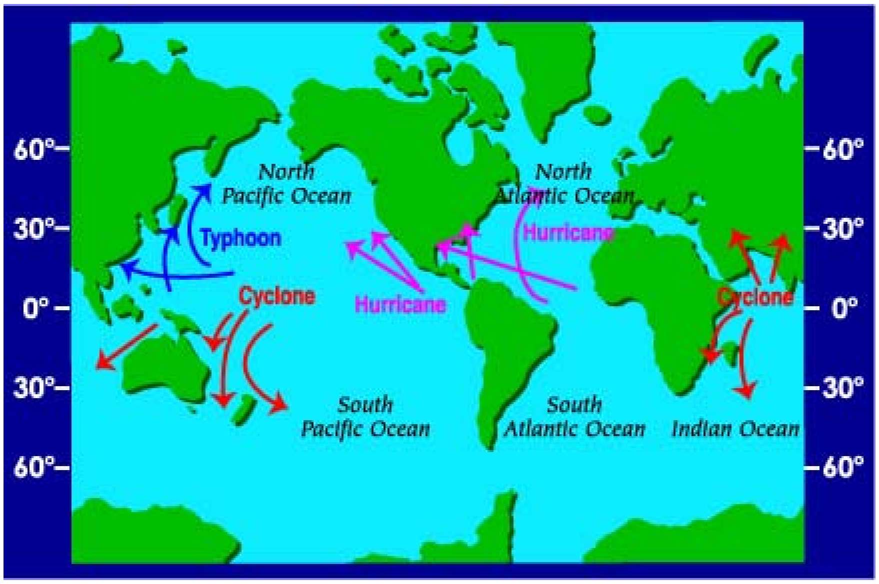


Fig.2-1 Hurricane/Typhoon/Cyclone around the world
(Source: http://www.newmediastudio.org)

The severity of the hurricane is usually measured on the *Saffir-Simpson Hurricane Scale* that classifies hurricanes into five categories. Hurricanes reaching Category 3 and higher are considered major hurricanes because of their potential for loss of life and extensive physical damage. The classification of hurricanes based on the wind speed is shown in table 2-2.

Table 2-2. Saffir-Simpson hurricane scale

Category	Wind Speed	Damage
I	74-95 mph	Minimal
II	96-110 mph	Moderate
III	111-130 mph	Extensive
IV	131-155 mph	Extreme
V	> 155 mph	Catastrophic

Since the 1880s, only two category 5 hurricanes have struck the United States: in 1935, an unnamed storm that hit the Florida keys and in 1969 Hurricane Camille that swamped the Mississippi coast.

2.2 Hurricane Floyd

Hurricane Floyd was a monster category 4 hurricane, with a diameter almost 600 miles wide, which at one point churned with 155 mph winds, almost a rare category 5. Its path roughly paralleled the Atlantic US coastline remaining offshore from Miami, Florida to its landfall near Cape Fear, North Carolina as a category 2. For the United States, nearly the entire Atlantic coast from Miami to Plymouth, Massachusetts was put under a hurricane warning (PBS&J 2000).

At least 3.5 million people from four states--- Florida, Georgia, South Carolina, and North Carolina—evacuated during Hurricane Floyd. It was the largest evacuation in U.S. history. Fig 2-2 shows the track of hurricane Floyd.

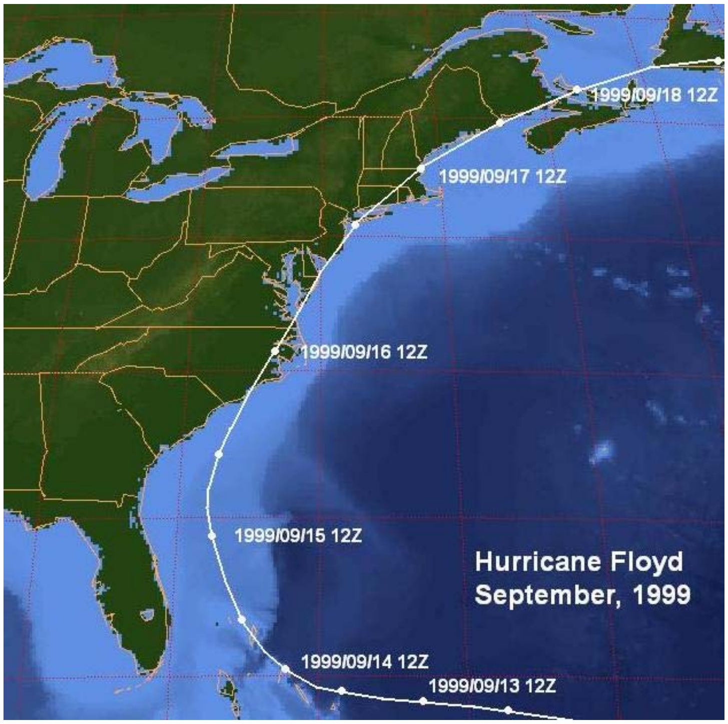


Fig.2-2 The track of Hurricane Floyd

2.3 Trip Distribution

There are many methods nowadays for travel demand forecasting. The Urban Transportation Modeling System (UTMS) represents a sequential model structure with 4 steps: trip generation, trip distribution, mode choice and trip assignment. There is a lot of research interest in activity-based model. Discrete choice models (logit models) are often used to model destination choice, mode choice or route choice in transportation demand modeling. Integrated land-use and transportation models recognize the importance of the interaction of transportation and society. In spite of these new developments, the 4-step UTMS model remains the dominant modeling method used in practice and can be easily implemented using existing planning software.

The focus of this study is on the trip distribution process in the 4-step trip-based model. Various types of trip distribution models exist, among these are growth factor models (Fratar model, Detroit model, etc.), the gravity model, intervening opportunity model, and the competing intervening opportunity model.

Trip distribution is, in essence, a destination choice process that utilizes the productions/attractions information to obtain an origin-destination trip table.

2.3.1 Destination Choice in Hurricane Evacuation

The choice of an evacuation destination tends to be modeled in one of the following ways (Southworth 1991):

- Evacuees will choose the closest destination (in terms of distance or travel time) beyond the at-risk area.
- Evacuees will head for pre-specified destinations, according to an established evacuation plans.
- Evacuees will display some degree of dispersion in their selection of destinations, depending on such factors as location of friends and relatives, the characteristics of the hazard, and the traffic conditions on the network at the time they are evacuating.

The first assumption may work effectively in modeling small urban systems or rural evacuations when the hazard is approaching rapidly. Some large cities within the US have well-publicized evacuation routes which may favor the second approach above. (Mei, 2002). Southworth suggested that a good plan supplemented by effective policing of traffic flow could make this option the best method for evacuation. The third option, while more complicated, is closer to reality, especially for hurricane evacuation. In this paper, we built our model based roughly on the basic assumption of the third option.

The destinations of almost all hurricane evacuation conducted in the past have been recorded and studied. It has been found that friends or relatives and hotels/motels are the most common destinations during hurricane evacuation. In southwest Louisiana during Hurricane Andrew, these two destinations comprised 64% and 13% respectively of all evacuation trips (Irwin et al. 1995). In Alabama, these two figures were 55-68% and 17-26% during hurricanes (Mei 2000). In North Carolina, they were 68.8% and 16.2% (RDS 1999). The percentage of the evacuees who went to public shelters was only 12%, 3.8% and 6.4%, respectively in the three studies mentioned above. Many factors, including the severity of the hurricane, income level and the distance from the hurricane, will affect this ratio.

2.3.2 Evacuation Modeling Development and State-of–the-art

Many simulation packages have been developed to deal with evacuation problems. HMM Associates and Urbanik used NETSIM to estimate evacuation time for a nuclear plant area in the early 1980s. The drawbacks of NETSIM in application to evacuation analysis are its limited capacity to handle large regional networks and its lack of a dynamic route selection model (Mei 2002). The NETVAC model developed by Sheffi and Mahmassani was aimed specifically at nuclear evacuation analysis. Other simulation packages that have application in evacuation include DYNEV developed by KLD Associates, and MASSVAC by Hobeika et al. (Mei 2002).

One of the recently developed evacuation analysis tools is the Oak Ridge Evacuation Modeling System (OREMS), which uses macro-simulation to reproduce link flows based on an adaptation of CORSIM. This model was developed to simulate traffic flow during various defense-oriented emergency evacuations. The model output includes clearance times, operational traffic characteristics and evacuation routes.

Another recent macro-level evacuation modeling and analysis system is Evacuation Travel Demand Forecasting System (PBS&J 2000). At the heart of the model is a web-based travel demand forecasting system that anticipates evacuation traffic congestion and cross-state travel flows for North Carolina, South Carolina, Georgia and Florida. This model requires input of destination percentages for affected counties based on past experience.

From the review of the development and state-of-the-art of evacuation modeling, a more comprehensive and theoretically sound travel demand model will be important and highly desirable.

2.4 Intervening Opportunity Model

For the time being, the gravity model is still the most frequently used trip distribution method in transportation planning. Few agencies have applied the intervening opportunities model, and there appear to be two major reasons for this:

1. The lack of software and expertise to calibrate and apply the model.
2. Insufficient data and research effort into the calibration of the model.

However in the case of hurricane evacuation, the opportunity model may have an advantage over the gravity model in the manner in which impedance is handled within the formulation. In the gravity model, travel distance or travel time is the measure of impedance used to control the distribution of destinations. However, in hurricane evacuation, people are not as concerned about the proximity of destinations as they are about getting out of the path of the oncoming hurricane and finding refuge at the home of a friend or relative, or at a hotel, motel or public shelter.

Stopher and Meyburg (1975) state that, in concept, the intervening opportunity model is a somewhat more satisfying formulation of trip distribution than gravity model. The model has a “ stronger conceptual base, and attempts to address the problem of individual behavior.” (Stopher and Meyburg 1975)

2.4.1 Formulation

2.4.1.1 History

The formulation of the opportunity model originated with Stouffer (Stouffer 1940), and was applied to population migration. The model was originally formulated as:

$\delta P = K/V$, or

$P = K \ln V + C_1$

Where V= total number of opportunities within a radius R from the town of origin

P= number of migrants who find destinations within a radius R from their starting place

The introduction of the opportunity model into transportation planning was due to Morton Schneider (1959). The Chicago Area Transportation Study (CATS) team, of which Schneider was a part, conducted much of the early development work on trip distribution models.

2.4.1.2 Classical Formulation

The first assumption of an intervening opportunity model is that trip makers consider potential destinations sequentially, in order of their impedance away from the origin (Rogerson 1993).

Let i = origin zone

j = j^{th} destination in order of travel impedance(distance or time) from the origin zone

A_j= number of destination opportunities in the j^{th} zone

V_j=the sum of destination opportunities available from the origin zone to the j^{th} zone, as ranked by travel impedance from the origin zone

U_j=probability of traveling beyond zone j

L= the constant probability of accepting a destination if it is considered

P (V_j)= probability of finding an acceptable destination in V_j opportunities.

P (A_j)= probability of finding an acceptable destination in A_j opportunities of zone j

Assuming a constant L, we have

$U_j=U_{j-1}(1-LA_j)$

$-LA_j=(U_j-U_{j-1})/U_{j-1}$

but $A_j=V_j-V_{j-1}$

Hence, $-L(V_j-V_{j-1})=(U_j-U_{j-1})/U_{j-1}$

Assuming many destinations, U and V can be taken as continuous functions

Hence,

$$-LdV=dU/U \qquad (1)$$

Integrating both sides, we have $U=Ke^{-LV}$, where K is a constant of integration

The number of trips from zone i which terminate in zone j will be the total number of trips originating from i times the probability that the trip ends in zone j.

Hence,

$T_{ij}=O_i\,(U_j-U_{j-1})$

$U_j=Ke^{-LVj}$

Hence,

$T_{ij}=KO_i\,(e^{-LVj-1}-e^{-LVj})$

Applying the production constraint, assuming all trips from origin i are distributed, and there are n zones, we have

$$\sum_j T_{ij} = O_i K(1-e^{-LVn}) = O_i$$

Hence,

$$K = \frac{1}{1-e^{-LVn}}$$

so we get the common formulation of the intervening opportunity model:

$$T_{ij} = \frac{O_i(e^{-LV_{j-1}} - e^{-LV_j})}{1-e^{-LV_n}} \qquad (2)$$

It is known as the *forced intervening opportunity model*, which is a singly constrained model.

If we use another constraint instead, the constraint that all trips must be made, we get the *free intervening opportunity model* (Stopher and Meyburg 1975) where the probability of traveling beyond the origin, U_0, is equal to 1.

$U_0=Ke^{-LV_0}$

Hence K=1, and

$$T_{ij} = O_i(e^{-LV_{j-1}} - e^{-LV_j}) \qquad (3)$$

2.4.1.3 A Formulation that compares with the Gravity Model

This finding of the similarity of gravity model and intervening opportunity model is due largely to CATS, and explained in another fashion by Zhao et al. (Zhao et al. 2001).

Using the free intervening opportunity model, and equation (3)

$V_j = V_{j-1} + A_j$

Hence, $T_{ij} = O_i(e^{-LV_{j-1}} - e^{-LV_j}) = O_i(1 - e^{-LA_j})e^{-LV_{j-1}}$

If L is small, on the order of 0.1 or less, then $1-e^{-LA_j}$ is nearly equal to LA_j, (Eash, 1984) therefore,

$$T_{ij} \approx O_i A_j L e^{-LV_{j-1}}$$

A factor f_i is applied to force all origin trips to be distributed.

$$T_{ij} = f_i O_i A_j L e^{-LV_{j-1}}$$

$$\sum_j T_{ij} = \sum_j f_i O_i A_j L e^{-LV_{j-1}} = f_i O_i \sum_j A_j L e^{-LV_{j-1}} = O_i$$

$$\Rightarrow f_i = \frac{1}{\sum_j A_j L e^{-LV_{j-1}}}$$

Therefore,

$$T_{ij} = O_i \left\{ \frac{A_j e^{-LV_{j-1}}}{\sum_k A_k e^{-LV_{j-1}}} \right\} \qquad (4)$$

Replacing exp $(-LV_{j-1})$ with F_{ij}, it then has the form of a singly constrained gravity model.

$$T_{ij} = O_i \left\{ \frac{A_j F_{ij}}{\sum_k A_k F_{ik}} \right\},$$ where F_{ij} is the friction factor in the gravity model.

If the friction factor function is assumed to be a gamma function, then

$$F_{ij} = \alpha d_{ij}{}^{\beta} e^{-\gamma d_{ij}}$$

Setting $d_{ij} = V_{j-1}, \alpha = 1, \beta = 0, \gamma = L$ respectively, we have $F_{ij} = e^{-LV_{j-1}}$, the functional form of the friction factor assumed above produces a singly constrained gravity model. A doubly constrained intervening opportunity model can be interpreted in similar fashion (Eash 1984). Note that in these assumptions, the gamma function is reduced to an exponential function and distance is replaced by the number of opportunities passed up.

The intervening opportunity model is shown to be a unique kind of gravity model and can, subsequently, be calibrated as a gravity model as demonstrated later.

2.4.2 Application and Evaluation of the Intervening Opportunity Model, Past Experience

The intervening opportunity model was used in two major studies in Chicago and Pittsburgh. The Chicago Area Transportation Study (CATS) was among the first users and has been the vanguard in the research and application of the procedure.

David (1961) compared the intervening opportunity model with the gravity model using the survey data from the Pittsburgh Area Transportation Study. The study showed that the opportunity model had smaller prediction error (with larger R^2 values), and that it simulated trip distribution reasonably well and somewhat better than the gravity model. In his report (David 1961), the opportunity model's value in terms of producing realistic results for a transportation study was quoted as being "certainly at least on a par with that of the gravity model". He suggested that the opportunity model comes closer than the gravity model to producing results that have a logical basis in human behavior. However he went on to point out that neither method can be considered wholly satisfying.

The U.S. Bureau of Public Roads carried out a comparative evaluation of different trip distribution procedures on the Washington D.C. data in the 1960s (Pyers 1966). Four trip distribution models, the Fratar model, gravity model, intervening opportunities model and competing opportunity model were compared. The intervening opportunity model performed very well and was calibrated with little difficulty. Though the overall accuracy of the gravity model proved to be slightly better than the accuracy of the intervening opportunity model in base year simulation and in forecasting ability, the opportunity model had the advantage that no socioeconomic adjustment factors were necessary. In the opportunity model calibration process, trip ends were stratified into long residential, long non-residential and short. Separate L values were developed through an iterative process to ensure satisfactory average trip length, trip length frequency, etc for each trip stratum.

In 2001, Florida International University calibrated an intervening opportunity model for Palm Beach County using 1999 survey data (Fang et al. 2001). The model was compared with the gravity model currently used in Florida. TRANPLAN was used to build the model. The intervening opportunity model that was calibrated performed slightly better than the gravity model for the HBW (Home Based Work) purpose but not better for the other trip purposes.

For the time being, there are only a few studies that employ the intervening opportunity model. The gravity model is still regarded as the dominant method for trip distribution. But as the understanding of the intervening opportunity model grows and as the new software for its application is developed, it is believed that the model will become a more and more attractive alternative.

2.4.3 The Similarity of the Gravity Model and Opportunity Model

The above discussion has already revealed some of the similarities of the gravity and opportunity models. CATS has undertaken considerable research on the opportunity model and compared it to the traditional gravity model. It has been shown that the two models are "fundamentally the same" (Eash 1984). For example, the two models can both be derived from entropy maximization theory. According to Eash, the only difference between the two models lies in how the disutility of travel is viewed. In the gravity model, this disutility is set as a strict function of travel cost; while in the opportunity model travel disutility is a function of the difficulty to satisfy a trip purpose.

Willis (1986) has built a flexible gravity-opportunities model for trip distribution. It lets the data decide which combination of features of the two models fits better, but the computational complexity of his model is considerable. Goncalves and Ulyssea-Neto (1993), and Diplock and Openshaw (1996) have also developed hybrid gravitational-opportunity models.

The doubly constrained gravitational-opportunity model is generally shown as:

$$T_{ij} = A_i B_j O_i D_j e^{-(\beta^* c_{ij} + \lambda \omega_{ij})}$$

Where O_i and D_j are productions and attractions, c_{ij} is a measure of the spatial separation between zones i and j; ω_{ij} is a measure of the number of intervening opportunities between zones i and j; and $\lambda$is the parameter associated with the intervening opportunities.

2.4.4 Calibration Method and Model Performance

The determination of the parameter set, in a way that estimates given by the model are the ones that best fit the observed data is a process called calibration. The calibration of the model decides the accuracy and hence the usefulness of the model. Great emphasis is placed on the method to calibrate the parameters in the model. In the intervening opportunity model, the parameter to be calibrated is the L-value. The L is the probability of accepting a destination if it is considered.

2.4.4.1 Maximum Likelihood Method

Rogerson has derived the maximum likelihood estimator for the intervening opportunities model (1992). The major restriction of his method is an assumption that the spatial distribution of opportunities is uniform, which is unrealistic in transportation, and particularly in evacuation. Eash (1984) also used the method of maximum likelihood for calibration of the intervening opportunity model without the assumption of uniform opportunities and has successfully coded a binary search program that solves for L values.

Eash (1984) formulated a likelihood function L_i for zone i as:

$$L_i = \prod_{j=1}^{n} P_{ij}^{N_{ij}}$$

where L_i= the likelihood value for zone i.

P_{ij}= probability of an interchange between zone i and zone j estimated by the distribution model.

N_{ij}= number of survey trip interchanges from zone i to zone j.

n= total number of zones

Substitute the probability of trip interchange by the opportunity model:

$$L_i = \prod_{j=1}^{n} \left\{ e^{-LV_{j-1}} - e^{-LV_j} \right\}^{N_{ij}}$$

By summing over all the destination zones and taking the log of the likelihood function, we have the log likelihood to maximize:

$$\ln L_i = \sum_{j=1}^{n} N_{ij} \ln \left\{ e^{-LV_{j-1}} - e^{-LV_j} \right\}$$

A simple one dimensional search algorithm can solve the above problem for value of L.

2.4.4.2 Graphical Method

One convenient method of calibration involves the use of a graphical plot (Stopher and Meyburg 1975). This can be explained as follows:

Define V as the intervening opportunity before a zone j, and U as the probability of traveling beyond that zone. Let P be the probability of a trip terminating in volume V, that is, P=1-U and dU=-dP. Substituting these relations into equation (1), we have

(1-P) LdV=dP

dP/(1-P)=LdV,

Integrating both sides of the equation, we have the relationship:

-ln (1-P)=LV+k

Hence we can evaluate P and V for a series of time intervals from each origin zone and use regression techniques to obtain the values of L. This method of calibration is simple and straightforward. It can evaluate multiple L values for different origins and different travel distances.

2.4.4.3 Calibration Method Using Average Trip Length

Stopher (Stopher and Meyburg 1975) also presented a calibration method that uses the average trip length to estimate the parameter L. This calibration method is based on two assumptions:

1. Trip end density is constant and extends to infinite distance.
2. The time ranking of possible destinations can be replaced by a distance ranking without loss of accuracy.

The result is equation (5):

$$L=1/(4\rho r^2) \qquad (5)$$

L is the calibrated parameter and has the units of 1/trip ends. ρ is the trip-end density and r is the mean trip length.

This method has the problem of defining a trip-end density and is not satisfactory when the trip-end density is highly variable.

Stopher (1975) mentions that, one calibration method that is often used in practice is an iterative process to solve the equation below:

$$L = \frac{L\sum_j d_{0j}(e^{-L_j} - e^{-LV_{j+1}})}{r_0(1-e^{-LV_n})} \qquad (6)$$

Where d_{0j} is the distance between origin 0 and destination j, and r_0 is the mean trip distance from the origin zone 0. A number of iterative procedures are available to solve this equation; the most efficient procedure is a hill-climbing linear programming method. (Stopher and Meyburg 1975). This method can solve for individual L for different origins and also for different travel distances.

The Chicago Area Transportation Study (CATS) used the above average trip distance method to calibrate the L value. Air distance was used for ease of computation. An initial value for L was chosen and a value for average trip length computed. Estimated and observed average trip lengths were then compared and the estimation of L factored accordingly. The observed average trip length is usually the average for a sample of trips taken from the total population of trips.

2.4.4.4 Calibration Using Existing Software Package of Gravity Model

Since the intervening opportunity model is proven to be a unique form of the gravity model, we can also use existing programs to calibrate gravity models to calibrate the opportunity model. Software to accomplish this can be easily found, for example, TranPlan or TransCAD both can be adapted to allow the calibration of the opportunity model.

2.4.4.5 New Development in CATS (Chicago Area Transportation Study)

CATS uses the intervening opportunity model for trip distribution. It was revised recently to incorporate new advances in the area. (CATS, 2003) A key modification was to change the definition of the impedance measure from simply highway travel time to the combined time and cost for both the highway and transit system. The combined impedance measure was called the LogSum variable.

The second modification was in the development of L-values (CATS, 2003). The L-value was regarded as a measure of how “selective” trip makers were toward “accepting” an opportunity. Typically the L-values are low in the center city where there are many opportunities and a person can be more selective and high in low-density suburban areas where this is less true. Previous L-values were developed based on the location of the traveler. These locations were primarily identified as the counties in the region and the city of Chicago. The new procedure adopted by CATS relates the L-values to the number of opportunities that can be reached within a given generalized cost boundary. Thus the L-value is now related to the transportation service level (the generalized cost) and the land use form (the number of opportunities) which are explicit measure of transportation service level (CATS 2003).

2.4.4.6 More Theoretical Calibration Methods and Measures of Model Performance

Goncalves et al (2001) published a report about the calibration methods of the gravity model, opportunity model and gravitational-opportunity model. Several kinds of calibration methods are cited in the report, such as maximum likelihood (Evans, 1971; Goncalves and Ulyssea-neto, 1993;Yun and Sen, 1994), Mean Sum of Squares Error (Diplock and Openshaw, 1996) and the use of the phi-normalized statistic (Smith and Hutchinson, 1981) etc. Goncalves (2001) found that models performed better when using the maximum likelihood calibration method, and taking into account the relative ease of its application and the fact that no numerical difficulties arose during the calibration process of this method, it was suggested as the best method for the calibration of all the models. After calibration the numerical difficulties and the model performance were evaluated. The models performance can be measured by the extent to which the trip-length frequency distributions of the observed and modeled trips are similar. Several goodness-of-fit measures were suggested (Goncalves 2001):

The Dissimilarity Index (DI) is defined by:

$$DI = \frac{50}{T^*}\sum_{ij}\left|T_{ij}^{\ *} - T_{ij}\right|$$

Where T_{ij}= number of trips estimated by cell

$T_{ij}^{\ *}$=number of trips observed by cell

T^*=total number of observed trips, $T^* = \sum T_{ij}^*$;

The dissimilarity index compares the percentage difference in groups of two distributions; it is often used in social science, with a minimum value of 0, indicating two identical distributions, and a maximum value of 100. The lower the value, the better fit we have for the two distributions.

The Normalized Absolute Average Error (NAAE) is defined by:

$$NAAE = \sum_{ij}\left|\frac{T_{ij}^{\ *} - T_{ij}}{\overline{T^*}}\right|$$

Where $\overline{T^*}$ =average number of trips observed by cell, calculated by

$\overline{T^*} = \frac{\sum T_{ij}^*}{ncel}$, ncel= number of cells

The Phi-normalized statistic is defined by:

$$f = \sum_{ij}\frac{T_{ij}^*}{T^*}\left|\ln\left(\frac{T_{ij}^*}{T_{ij}}\right)\right|$$

The Root Mean Square Error (RMSE) is defined by:

$$RMSE = \left[\sum_{ij}\frac{(T_{ij}^{\ *} - T_{ij})^2}{ncel}\right]^{1/2}$$

And, the Chi-square error is defined by:

$$\chi^2 = \sum_{ij} \frac{(T_{ij}^* - T_{ij})^2}{T_{ij}}$$

2.4.5 Goodness-of-fit Measure for Comparison of Geographic Interaction Models

In the light of the research on goodness of fit by Knudsen and Fotheringham (1986) and Fotheringham and Knudsen (1987), a reasonable strategy to evaluate spatial interaction models would be to employ a combination of two of the following three statistics: R^2, Information Gain and SRMSE (Standard Root Mean Square Error). The two statistics and another useful statistics of "coincidence ratio" are explained in detail as follows.

2.4.5.1 Information Gain

Information gain is calculated as:

$$I = \sum_i \sum_j T_{ij} \ln(T_{ij} / T_{ij}')$$

It has a lower value of zero corresponding to a perfect set of predictions and upper limit of infinity.

The cells with zero estimated value would not be included in the calculation.

2.4.5.2 SRMSE

A problem with the commonly used Root Mean Square Error (RMSE) is that it is not standardized by any measure of variance; thus, if the variance in the variable to be predicted is large, the RMSE is likely to be large also, and *vice versa,* making comparisons between RMSE problematic, even for different classes of the same data set. Correspondingly, the RMSE can be small when there is no correlation between the target and estimated proportions. The solution is to use Standardized RMSE (SRMSE).

SRMSE is calculated as

$$\text{SRMSE}=(1/T)[\sum_i \sum_j (T_{ij} - T_{ij}*)^2 / ncel]$$

It has a lower limit of zero, indicating a completely accurate set of predictions and an upper limit that, although variable and dependant upon the distribution of observed flows, is usually 1.0. (Fotheringham and O'Kelly 1989)

2.4.5.3 Coincidence Ratio

In order to compare the shapes of the trip length distribution from the models, we used the coincidence ratio: (Fang et al. 2001)

$$\text{Coincidence}=\sum_{t=1}^{T} \min\{\frac{f^m(t)}{F^m}, \frac{f^0(t)}{F^0}\}$$

$$\text{Total}=\sum_{t=1}^{T} \max\{\frac{f^m(t)}{F^m}, \frac{f^0(t)}{F^0(t)}\}$$

$$\text{Coincidence ratio}=\frac{Coincidence}{Total}$$

Where $f^m(t)$=frequency of trips at time t from model

$f^0(t)$= frequency of trips at time t from survey data

F^m = total trips distributed from model

$F^0(t)$= total trips from survey data

The coincidence ratio lies between zero and one, with zero indicating two disjoint distributions and one indicating identical distribution.

2.4.6 Conclusion

Intervening opportunity model is an interesting method in the trip distribution study of the four-step transportation planning process, it deserves more attention than it now possesses and has large potential that we have not fully made use of. The application and calibration method of this model were discussed.

CHAPTER 3. DATA

3.1 Survey Data

The U.S. Army Corps of Engineers commissioned a survey to obtain the Hurricane Floyd evacuation data. The survey was conducted by Professor Earl J. Baker of Florida State University to study the travel behavior in hurricane evacuation for future planning purposes.

The questionnaire contained 91 questions, which include questions such as "Did you go to a public shelter, a friend or relative's house, a hotel, or somewhere else?", "In what city is that (evacuation destination) located?", "In which state is that located?" etc.

3.2 Data Cleaning

1887 telephone interviews were conducted in Charleston, Beaufort and Myrtle Beach areas in South Carolina. These are the only three origins of evacuation in the model. The data were cleaned and reformatted to serve as the input to the model. Destinations were observed in South Carolina, North Carolina, Georgia, and Tennessee. Origins and destinations were identified by county or city.

In the questionnaire, the destinations are classified into several categories, which are shown below (question 9 in the questionnaire):

9. Did you go to a public shelter, a friend or relative's house, a hotel, or somewhere else?
   - 1 Public shelter (Red Cross)
   - 2 Church
   - 3 Friend/relative
   - 4 Hotel
   - 5 Workplace
   - 6 Mobile home park clubhouse
   - 7 Other, specify:
   - 9 Don't know

Table 3.1 shows the evacuation destinations in the survey, including numbers by type and by origin.

Table 3-1. Evacuation destinations in the survey

	Friends/ Relative	Hotel/ Motel	Shelter	Church	Work place	Mobile home	Other	Total
Beaufort	211	170	8	4	2	1	212	608
Charleston	259	122	6	4	3	1	232	627
Myrtle Beach	210	75	9	9	4	0	345	652
Total	680	362	23	17	9	2	789	1887

Only the data with the complete and correct information were used in this study. In total, 1042 households headed towards either homes of friends/relatives or hotels/motels, of which 941 households evacuated to the four states (SC, NC, GA, TN) considered in this study. Of the 941 households, 852 had complete and identifiable destination information. Thus, the percentage of valid data was 90.5%(852/941) after data cleaning.

Table3-2 shows the number of data actually used and the total number in the survey.

Table 3-2. Percentage of data utilization

	Friends/Relatives	Hotel/Motel	Total
Number Valid and Used	534	318	852
Number in Survey	680	362	1042
Data Usage	78.5%	87.8%	81.8%

3.3 Separation of the Data

There are three major destination choices recorded in Hurricane Floyd evacuation data: 1) Homes of Friends or Relatives; 2) Hotels or Motels; and 3) Public shelters. After investigation of the data, the data for the shelters was found to be insufficient to build a separate model. So the data were separated according to the type of the destinations, and then models were built for the destination of homes of friends or relatives (referred to as the population model in this thesis), and for the destination of hotels or motels (referred to as the hotel model), separately.

3.4 Geocoding of the Origins and Destinations

Lewis (1985) suggested that transportation modeling for evacuation is best performed on a county-by-county basis because evacuation orders are generally issued at county level. Thus, the origins and destinations of the evacuation trips in the Floyd data were assigned to the centroids of their counties or metropolitan cities. The geographical files (the US County file and the US Urban Clusters file) provided by the TransCAD package were used. The result was a new map or layer in TransCAD that contained all the nodes needed and the relevant information in the dataview.

The building of the joined county and metropolitan nodes layer is essential and explained as followed. First, the US county geographic file was opened, and then the origin and destination counties were selected in TransCAD and their centroids were exported. Similarly, the centroids of the Metropolitan cities that are contained in the data were exported. Finally, the two centroids file were added together as a new layer to the US county file, and the map was exported and saved as a combined nodes file. The maps of the nodes are shown in Fig. 3-1 to Fig. 3-3.

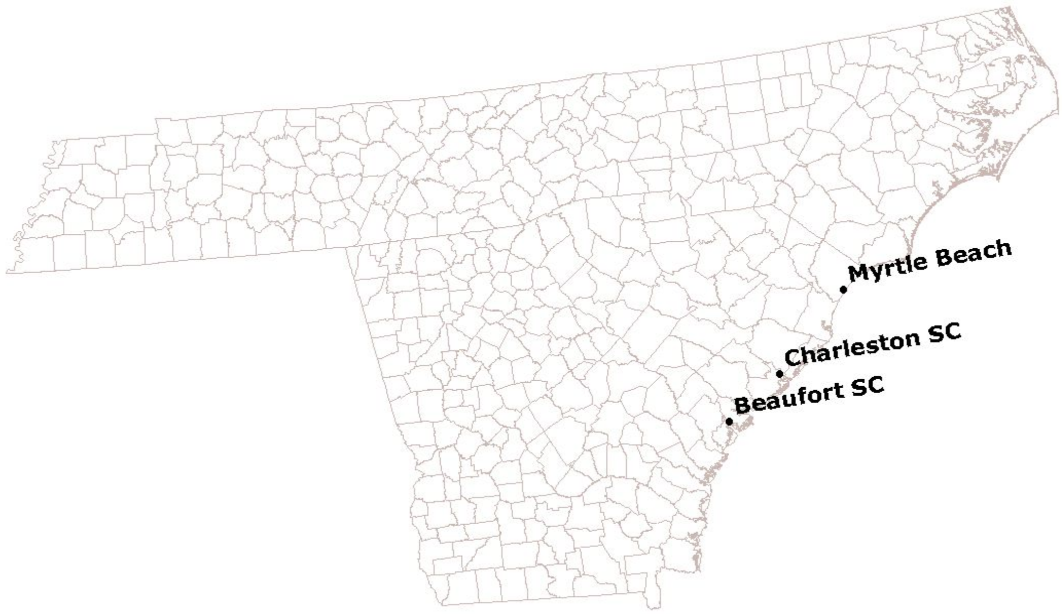


Fig.3-1 Three origins in the models (population model and hotel model)

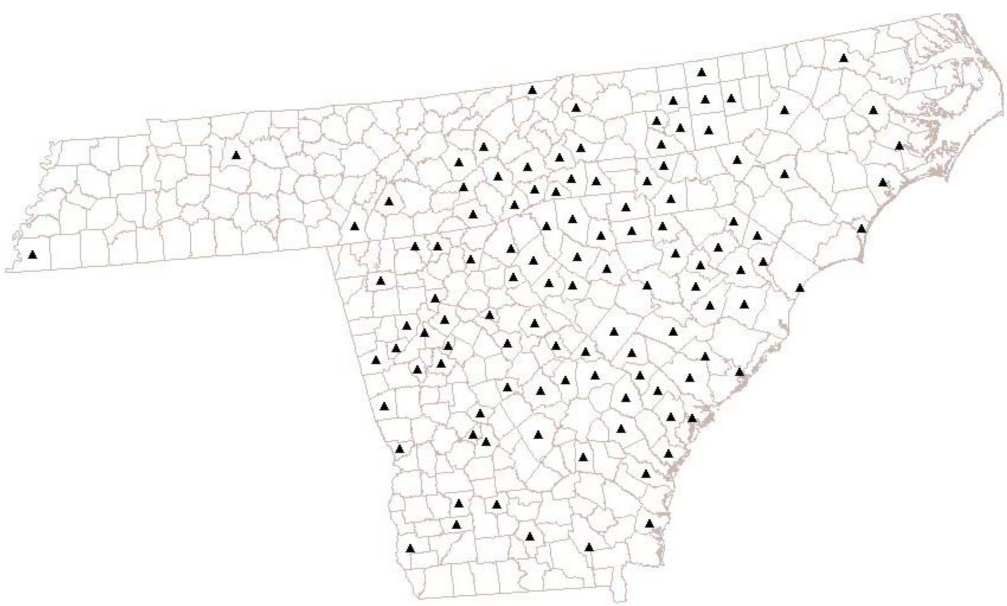


Fig.3-2 113 nodes (origins and destinations) in the population model

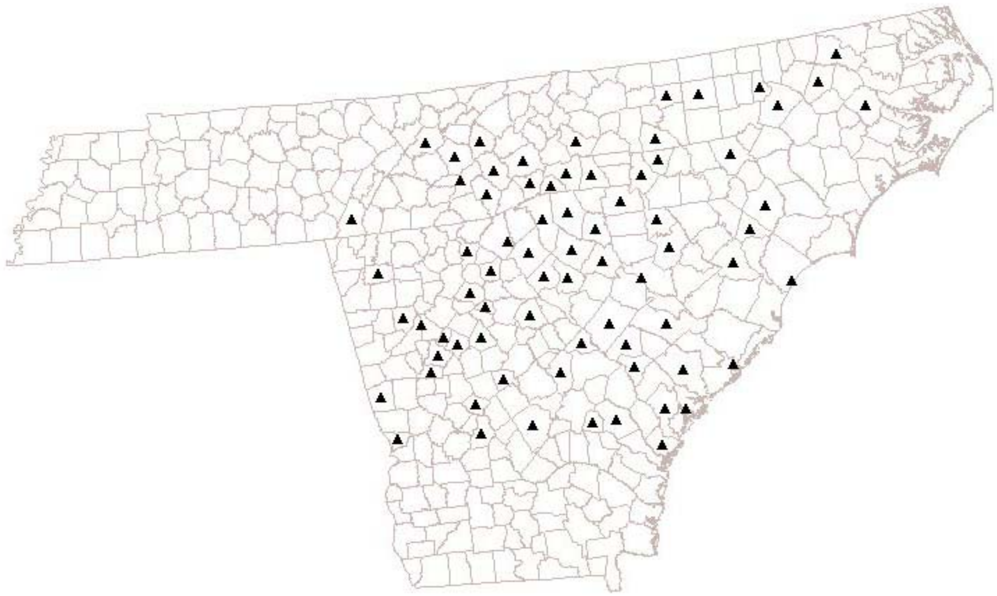


Fig.3-3 73 nodes (origins and destinations) in the hotel model
The detailed information about nodes is included in Appendix A.

3.5 Highway Network

The US highway file in the TransCAD was loaded as a line layer in the model. In this layer, a highway network was created in TransCAD. This network included interstate highway, US highway routes and state highway routes. The length, name and function type of each road link were included in the dataview, but there was no information about the travel speed or travel time of each road segment. This would not be a serious problem since we are mainly concerned about the planning of a large region or area, the distance of the destination can in this case be used as the impedance in the model input.

CHAPTER 4. MODELING IN TRANSCAD ENVIRONMENT: BUILDING AN INTERVENING OPPORTUNITY MODEL

4.1 Building the Intervening Opportunity Model

From Equation (4) it is known that the intervening opportunity model (IOM) can be formulated in a form that is similar to the gravity model. By replacing the friction factor function in the gravity model F_{ij} by exp ($-LV_{j-1}$), it becomes an intervening opportunity model.

The intervening opportunity model was used in this study to model the destination choice for hurricane evacuation. The TransCAD software package was used to calibrate and apply the model. An extended model that takes into account the effect of the path of the hurricane was built. The results of the opportunity model and the gravity model were compared and the performance of different models evaluated. The process is explained below.

4.2 Calibrating the IOM

4.2.1 Building an *O-D* Matrix from the Data

In the nodes layer of the model, a new matrix with all the nodes in both row and column was created. The number of trips observed for each origin-destination pair was calculated from the survey data. By updating the matrix with this trip table, an *O-D* matrix was obtained. The *O-D* matrices for the population and hotel model are shown in Appendix D. While trips originated from only 3 origins (Beaufort, Charleston, and Myrtle Beach), a square matrix is required in TransCAD for calibration. Thus, a 113×113 *O-D* matrix was established with zeros in the rows which were not origins.

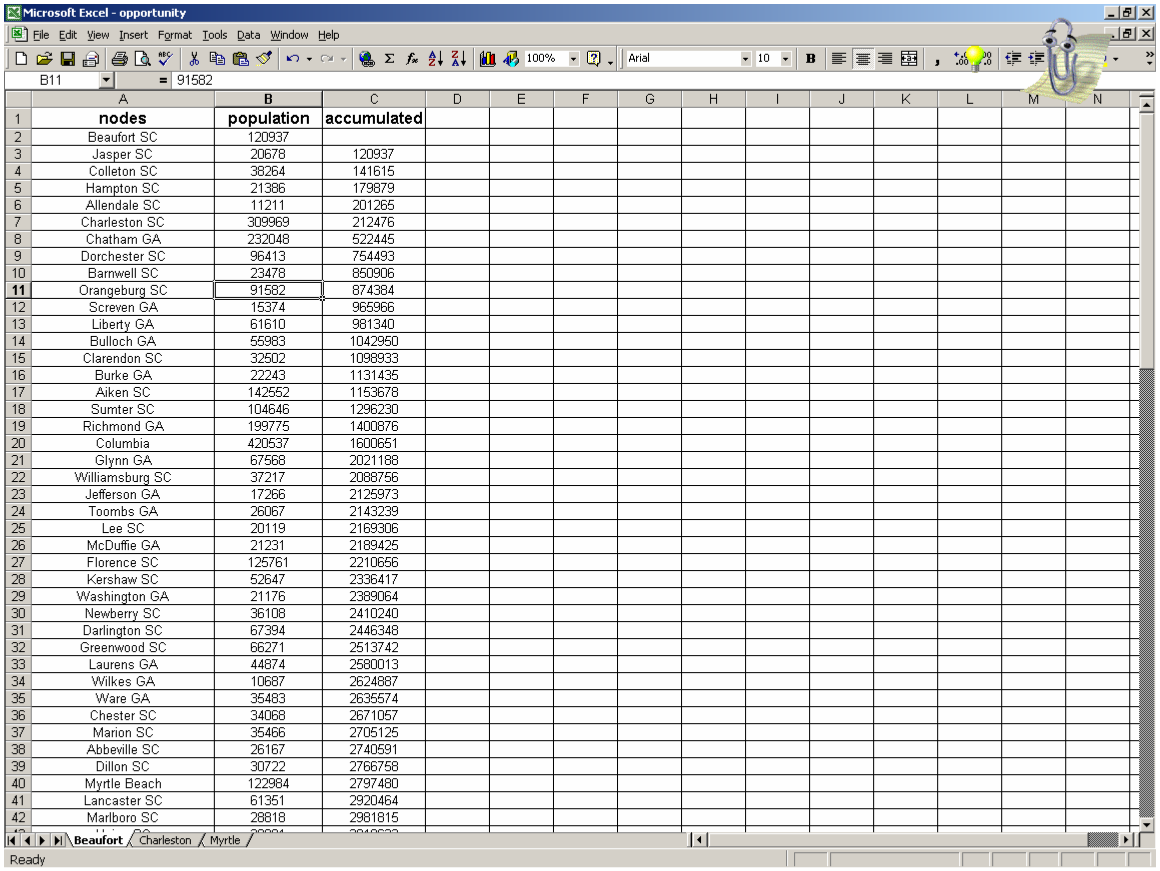
4.2.2 Building an Opportunity Matrix

All the destinations were ranked and sorted in terms of the travel distance (produced by multiple shortest path procedure in TransCAD) from each origin, then the total number of opportunities passed up to the destinations were summed up. Thus the opportunity matrix was constructed.

The opportunities used in the population model were selected to be the population of the county or city, since the chance that one may find a friend or relative in an area can be assumed to be proportional to the population in that area (Population of young children may not be regarded as a measure of attraction or opportunity for destinations, but the proportion of young children does not display much difference between areas. For convenience, the total population was used as the attraction.). The population of each county or city was obtained directly from TransCAD, which used the 2000 census data.

An example of the estimated intervening opportunities from Beaufort, South Carolina, are shown in Fig. 4-1.

Because this value of intervening opportunities is especially large (one city may have a population of several million), the direct application of the opportunity matrix produced computational overflow in TransCAD. To solve this problem, a scaling factor of 0.0001 to the opportunity value was used. It does not change the output of the model, the only effect it has is on the L-value, which must be multiplied by 10,000 later.



	A	B	C
1	nodes	population	accumulated
2	Beaufort SC	120937	
3	Jasper SC	20678	120937
4	Colleton SC	38264	141615
5	Hampton SC	21386	179879
6	Allendale SC	11211	201265
7	Charleston SC	309969	212476
8	Chatham GA	232048	522445
9	Dorchester SC	96413	754493
10	Barnwell SC	23478	850906
11	Orangeburg SC	91582	874384
12	Screven GA	15374	965966
13	Liberty GA	61610	981340
14	Bulloch GA	55983	1042950
15	Clarendon SC	32502	1098933
16	Burke GA	22243	1131435
17	Aiken SC	142552	1153678
18	Sumter SC	104646	1296230
19	Richmond GA	199775	1400876
20	Columbia	420537	1600651
21	Glynn GA	67568	2021188
22	Williamsburg SC	37217	2088756
23	Jefferson GA	17266	2125973
24	Toombs GA	26067	2143239
25	Lee SC	20119	2169306
26	McDuffie GA	21231	2189425
27	Florence SC	125761	2210656
28	Kershaw SC	52647	2336417
29	Washington GA	21176	2389064
30	Newberry SC	36108	2410240
31	Darlington SC	67394	2446348
32	Greenwood SC	66271	2513742
33	Laurens GA	44874	2580013
34	Wilkes GA	10687	2624887
35	Ware GA	35483	2635574
36	Chester SC	34068	2671057
37	Marion SC	35466	2705125
38	Abbeville SC	26167	2740591
39	Dillon SC	30722	2766758
40	Myrtle Beach	122984	2797480
41	Lancaster SC	61351	2920464
42	Marlboro SC	28818	2981815

Fig.4-1 Calculation of the intervening opportunities in the population model

In the hotel model, the number of opportunities is ideally the number of rooms or beds in hotels/motels in the destination county or city. However, this data is not readily available for every county or city. Some consulting companies have detailed information about number of beds in the hotel industry, but this information is generally regarded as a proprietary. After investigation, the data on the number of hotel/motel establishments on a county level as included in the 1997 Economic Census was used. This census is carried out every 5 years and the data is free and can be updated later on. So the number of hotel/motel establishments was selected to be the opportunity (attraction) for hotel model, which was obtained from the 1997 Economic Census under the category of Accommodation and Foodservices. Appendix E shows part of the census data.

An example of the estimated intervening opportunities from Beaufort and Charleston for the hotel model is shown in Fig. 4-2.

Microsoft Excel — hotsorted

	A	B	C	D	E	F	G	H	I
1		**Distance**	**No. of Accommodation**	**Accumulated**					**Accumulated**
2	Beaufort SC	0.00	51	0		Charleston SC	0.00	110	0
3	Jasper SC	42.21	16	51		Colleton SC	51.48	16	110
4	Colleton SC	45.89	16	67		Beaufort SC	73.94	51	126
5	Allendale SC	65.00	1	83		Orangeburg SC	73.96	35	177
6	Charleston SC	73.94	110	84		Jasper SC	83.02	16	212
7	Chatham GA	75.28	91	194		Allendale SC	94.20	1	228
8	Barnwell SC	83.69	3	285		Florence SC	101.03	22	229
9	Orangeburg SC	88.30	35	288		Barnwell SC	101.63	3	251
10	Bulloch GA	108.65	21	323		Columbia	112.45	97	254
11	Aiken SC	116.02	20	344		Myrtle Beach	114.95	303	351
12	Candler GA	121.33	4	364		Chatham GA	116.09	91	654
13	Richmond GA	126.36	52	368		Aiken SC	121.32	20	745
14	Columbia	130.83	97	420		Kershaw SC	130.55	11	765
15	Jefferson GA	140.26	2	517		Dillon SC	136.44	17	776
16	Florence SC	152.46	22	519		Richmond GA	146.12	52	793
17	Kershaw SC	156.41	11	541		Newberry SC	146.29	3	845
18	Newberry SC	164.67	3	552		Bulloch GA	147.21	21	848
19	Greenwood SC	168.84	9	555		Lancaster SC	161.83	3	869
20	Laurens GA	173.16	10	564		Candler GA	162.14	4	872
21	Wilkes GA	174.38	2	574		Robeson NC	163.56	35	876
22	Abbeville SC	184.13	3	576		Greenwood SC	168.19	9	911
23	Dillon SC	184.63	17	579		Jefferson GA	169.46	2	920
24	Myrtle Beach	186.74	303	596		Union SC	172.69	6	922
25	Lancaster SC	187.70	3	899		Laurens SC	176.45	9	928
26	Union SC	191.08	6	902		York SC	188.79	23	937
27	Baldwin GA	194.03	7	908		Abbeville SC	190.20	3	960
28	Laurens SC	194.83	9	915		Wilkes GA	194.14	2	963
29	York SC	207.17	23	924		Spartanburg SC	196.77	30	965
30	Robeson NC	210.07	35	947		Mecklenburg NC	201.86	157	995
31	Morgan GA	210.09	9	982		Moore NC	203.84	19	1152
32	Anderson SC	210.32	26	991		Greenville SC	207.63	70	1171
33	Clarke GA	214.16	36	1017		Cabarrus NC	210.44	13	1241
34	Spartanburg SC	215.15	30	1053		Laurens GA	211.83	10	1254
35	Mecklenburg NC	220.24	157	1083		Anderson SC	213.94	26	1264
36	Bibb GA	222.07	40	1240		Cleveland NC	222.10	9	1290
37	Franklin GA	225.48	3	1280		Baldwin GA	223.24	7	1299
38	Greenville SC	226.01	70	1283		Polk NC	228.30	7	1306

Fig.4-2 Calculation of intervening opportunities for the hotel model

4.2.3 Calibration of IOM in TransCAD

The procedure for the gravity model in TransCAD was used to calibrate the IOM. The calibration of trip distribution models requires the input of an *O-D* matrix and an impedance matrix (in this case, the opportunity matrix). An impedance function in the form of an exponential function was chosen. The model was calibrated for the parameter L of the intervening opportunity model. Instead of calibrated to the surveyed trip length distribution as in gravity model, the model was calibrated to the surveyed opportunity distribution.

First the geographic file of *US County* was opened, and on it layers of nodes and highway were added. In the *highway nodes* layer, a selection of origin destination nodes was carried out in this way: use " *Select by Value*" in the TransCAD menu, choose a matching field of "longitude", and create the selection set. This selection was useful in the calibration and application process. Then the *O-D* matrix and opportunity matrix were opened, and the trip distribution procedure-Gravity Calibration was applied. The impedance matrix was selected as the opportunity matrix that was built before. The result of the population model showed that the calibration procedure converges after 4 iterations. The parameter L=0.0021.

A similar procedure was applied to the hotel model. Except that for this model a scaling factor was not necessary since there was no overflow in calculation. The calibration of the hotel model converged after 6 iterations, the parameter L=0.0021

4.2.4 IOM Calibration Using Linear Regression

The intervening opportunity model can also be calibrated using a graphical method (refer to section 2.4.4.2). The relationship between P and V in the opportunity model is given by equation:

$$-\ln (1-P)=LV+ k$$

By plotting the graph of ln (1-P) and V, and applying linear regression, the slope in the graph is the calibrated value of parameter L. By comparing this L value and the L value calibrated by TransCAD, an idea of the validity of the methodology that was used to build the intervening opportunity model could be obtained. It can evaluate multiple L values for different origins and different travel distances. The calibration process on population model was completed. Figure 4-3 shows the result of calculation:

Microsoft Excel - data

E17 =SUM(D2:D17)

	A	B	C	D	E	F	G	H	I
1		Population	Accumulated	DATA	Accumulated	ln (1-P)			DATA
2	Beaufort SC	120937	**120937**	6	6	**-0.033152207**	Beaufort SC		
3	Jasper SC	20678	**141615**	1	7	**-0.038786025**	Abbeville SC	2740591	1
4	Colleton SC	38264	**179879**	2	9	**-0.050149784**	Aiken SC	1153678	8
5	Hampton SC	21386	**201265**	8	17	**-0.096941945**	Alamance NC	14337805	0
6	Allendale SC	11211	**212476**	1	18	**-0.102947969**	Allendale SC	201265	1
7	Charleston SC	309969	**522445**	1	19	**-0.108990284**	Anderson SC	3333801	2
8	Chatham GA	232048	**754493**	0	19	**-0.108990284**	Atlanta	7337372	38
9	Dorchester SC	96413	**850906**	1	20	**-0.11506933**	Baldwin GA	3054920	1
10	Barnwell SC	23478	**874384**	5	25	**-0.146031555**	Barnwell SC	850906	5
11	Orangeburg SC	91582	**965966**	2	27	**-0.158689952**	Berrien GA	5230452	0
12	Screven GA	15374	**981340**	1	28	**-0.16507975**	Bibb GA	4696949	1
13	Liberty GA	61610	**1042950**	1	29	**-0.171510641**	Bulloch GA	1042950	2
14	Bulloch GA	55983	**1098933**	2	31	**-0.184497836**	Buncombe NC	11561280	0
15	Clarendon SC	32502	**1131435**	0	31	**-0.184497836**	Burke GA	1131435	2
16	Burke GA	22243	**1153678**	2	33	**-0.197655921**	Burke NC	11095407	1
17	Aiken SC	142552	**1296230**	8	41	**-0.252091127**	Cabarrus NC	5432688	0
18	Sumter SC	104646	**1400876**	0	41	**-0.252091127**	Carroll GA	14527384	1
19	Richmond GA	199775	**1600651**	9	50	**-0.317095958**	Charleston SC	212476	1
20	Columbia	420537	**2021188**	24	74	**-0.514455392**	Chatham GA	522445	0
21	Glynn GA	67568	**2088756**	0	74	**-0.514455392**	Chester SC	2671057	0
22	Williamsburg SC	37217	**2125973**	0	74	**-0.514455392**	Clarendon SC	1098933	0
23	Jefferson GA	17266	**2143239**	1	75	**-0.523587875**	Clarke GA	3623218	0
24	Toombs GA	26067	**2169306**	1	76	**-0.53280453**	Clemson	5357452	0
25	Lee SC	20119	**2189425**	0	76	**-0.53280453**	Cleveland NC	5633862	0
26	McDuffie GA	21231	**2210656**	0	76	**-0.53280453**	Cobb GA	11802445	2
27	Florence SC	125761	**2336417**	3	79	**-0.560975407**	Cocke TN	15021038	0
28	Kershaw SC	52647	**2389064**	2	81	**-0.580206769**	Colleton SC	141615	2
29	Washington GA	21176	**2410240**	1	82	**-0.589962944**	Columbia	1600651	24
30	Newberry SC	36108	**2446348**	0	82	**-0.589962944**	Craven NC	14795804	0
31	Darlington SC	67394	**2513742**	0	82	**-0.589962944**	Cumberland NC	5730149	2
32	Greenwood SC	66271	**2580013**	3	85	**-0.619815907**	Darlington SC	2446348	0
33	Laurens GA	44874	**2624887**	1	86	**-0.629968279**	Davidson NC	11280620	0
34	Wilkes GA	10687	**2635574**	1	87	**-0.640224779**	Davidson TN	15693102	0
35	Ware GA	35483	**2671057**	1	88	**-0.650587566**	Davie NC	11767610	0
36	Chester SC	34068	**2705125**	0	88	**-0.650587566**	Dillon SC	2766758	0
37	Marion SC	35466	**2740591**	0	88	**-0.650587566**	Dorchester SC	754493	1
38	Abbeville SC	26167	**2766758**	1	89	**-0.661058866**	Dougherty GA	11184555	1
39	Dillon SC	30722	**2797480**	0	89	**-0.661058866**	Douglas GA	12440007	1
40	Myrtle Beach	122984	**2920464**	0	89	**-0.661058866**	Early GA	14647418	1
41	Lancaster SC	61351	**2981815**	0	89	**-0.661058866**	Fannin GA	14627620	1
42	Marlboro SC	28818	**3010633**	0	89	**-0.661058866**	Fayette GA	11427866	1
43	Union SC	29881	**3040514**	0	89	**-0.661058866**	Florence SC	2210656	3

Beaufort / Charleston / Myrtle

Ready

Fig.4-3 Calculation of P and V

The relationship between P and V for each origin is shown in plots in appendix B. The slope in the plot will represent the L parameter in intervening opportunity model. If the L value is constant, the plot will be a straight line with the same slope. From the three plots, it is observed that at opportunities value of less than 15,000,000, the plot is nearly a straight line. After 15,000,000, there is a sharp drop, that's probably due to the method of calculating the probability P. Since there are limited numbers of destination, and the probability is calculated with the surveyed destination distribution, the probability quickly approaches 100% around the furthest destination. That's why a sharp decline in the value of ln(1-P) is observed.

To obtain a single value of parameter L, the data for the three origins were pooled together. The plot is shown in Appendix B. The L value is approximately 2E-07. Then regression analysis was applied twice on the population model, once on the complete data, another on the data truncated at opportunities of 15,000,000. The regression output for the complete data is shown in table 4-1:

Table 4-1. Regression statistics to calibrate L: population model

Regression Statistics	
Multiple R	0.956889499
R Square	**0.915637513**
Adjusted R Square	0.915381869
Standard Error	0.344889998
Observations	332

	Coefficients	*Standard Error*	*T Stat*	*P-value*
Intercept	**0.133695409**	0.032830268	4.072321613	5.83E-05
X Variable 1	**-2.34751E-07**	3.9225E-09	-59.84723229	3E-179

The L value is approximately 2.3 E-07. Compared with the calibration result of TransCAD model, TransCAD output of L value is 0.0023, but since a scaling factor of 0.0001 was applied when building opportunity matrix, the actual L value may be 2.3 E-07. The calibration results using these two different methods are the same. This shows that the methodology for building the model is reliable and correct.

If only the truncated data with opportunities less than 15,000,000, are considered (for this part of data has displayed better linear relationship), the regression output is shown in table 4-2.

The L value calibrated this way will be 2.1E-07, which is a little bit smaller than the 2.3 E-07 obtained earlier.

Table 4-2. Regression statistics to calibrate L: truncated data

Regression Statistics	
Multiple R	0.967396669
R Square	**0.935856316**
Adjusted R Square	0.935649401
Standard Error	0.250894947
Observations	312

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	**0.049959849**	0.024589249	2.031776143	0.04302885
X Variable 1	**-2.14504E-07**	3.18953E-09	-67.25250805	6.013E-187

4.3 Applying the IOM

The model was applied on the original set of data to see if the model can replicate the survey data successfully. The productions and attractions for each node were calculated with the Floyd data. And with this production and attraction information and the opportunity matrix, using the calibrated model, a new trip table was produced as model output. Then observed and modeled trip table was compared to evaluate the performance of the model.

4.3.1 Adding Production and Attraction Information

Using the Aggregate function in the *O-D* matrix, the total trip production and attraction for each node was calculated. Then in the dataview of the nodes file, two new fields were created, one for production and one for attraction.

4.3.2 Apply the distribution model

In TransCAD, the procedure of trip distribution/gravity application was used. An exponential impedance function was chosen, production and attraction data were also provided. In the population model, the parameter L was set as 0.0021. It converged after 3 iterations. TransCAD produced an output matrix containing the calculated *O-D* flow. In the hotel model, the parameter L was also set at 0.0021. It converged after 3 iterations. Calculated *O-D* flow was obtained.

4.4 IOM Model Performance

4.4.1 Introduction

The performance of the regular intervening opportunity model was evaluated using several statistical and graphical techniques.

4.4.2 R^2 Statistics and Data Comparison

In this test, the trip rate table produced by intervening opportunity model was compared with the surveyed trip table. Each dot in the graph represents an origin destination pair, its value on the x-axis represents the number of surveyed trips, and its value on the y-axis is the trips produced by the model for the *O-D* pair. The R^2 statistics was used to assess the error of the model in prediction. The results are shown in Fig.

The R^2 statistics for population model is 0.85, while the R^2 for the hotel model is 0.74. The performance of the model is not excellent but acceptable given the many empty cells in the surveyed trip table. The population model has a higher R^2 value which indicates a better model performance.

a) Population model:

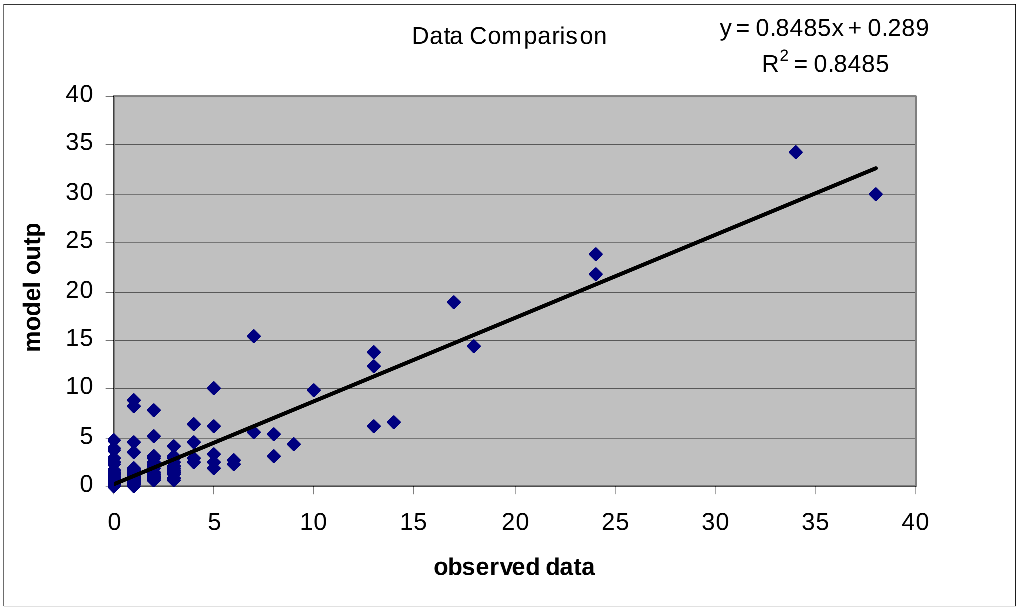


Fig.4-4 R^2 statistics for population model

b) Hotel model:

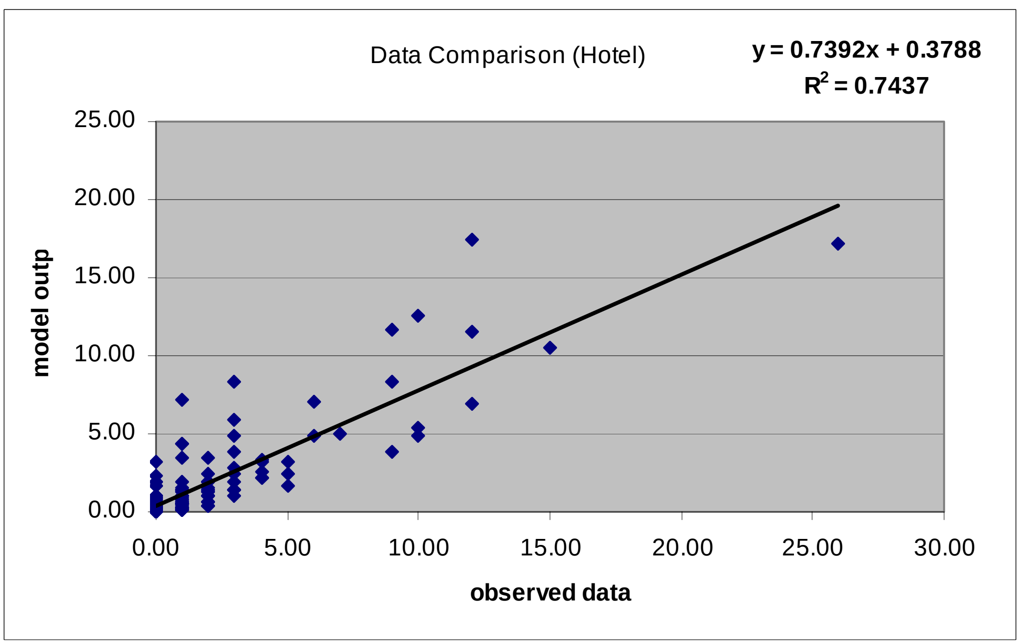


Fig.4-5 R^2 statistics for hotel model

The original surveyed data contain some *O-D* pairs that have no trips, while the model will assign trips to these pairs. This will cause the trips assigned to other *O-D* pairs to decrease. So in the graph, it looks like the model will underestimate the trips.

4.4.3 Trip Length Distribution

Travel distance was used as impedance sometimes, but to show trip length distribution, travel time was preferred. Since the speed in the link of the highway was not readily available, a uniform speed of 40 miles per hour was assumed to convert the travel distance impedance into travel time impedance. The trip length distribution curve was shown in Fig. 4-6 to Fig. 4-10, the curve was aggregated using a 1-hour travel time interval.

The intervening opportunity model has similar trip length distribution with the observed data, which is desirable.

The Trip Length Distribution curves of the model fit well with their observed counterpart except in the Myrtle Beach model as shown in Fig. 4-9. There are under prediction in the intrazonal trips and over prediction in other places. The survey data of Myrtle Beach differ with those of the other two origins in that it has more intrazonal trips, which is abnormal since the farther you are away from the hurricane, the safer. And for the intrazonal trips, we used the same origin and destination instead of the actual travel distance which may not reflect the detail underneath travel pattern.

a) Population model:

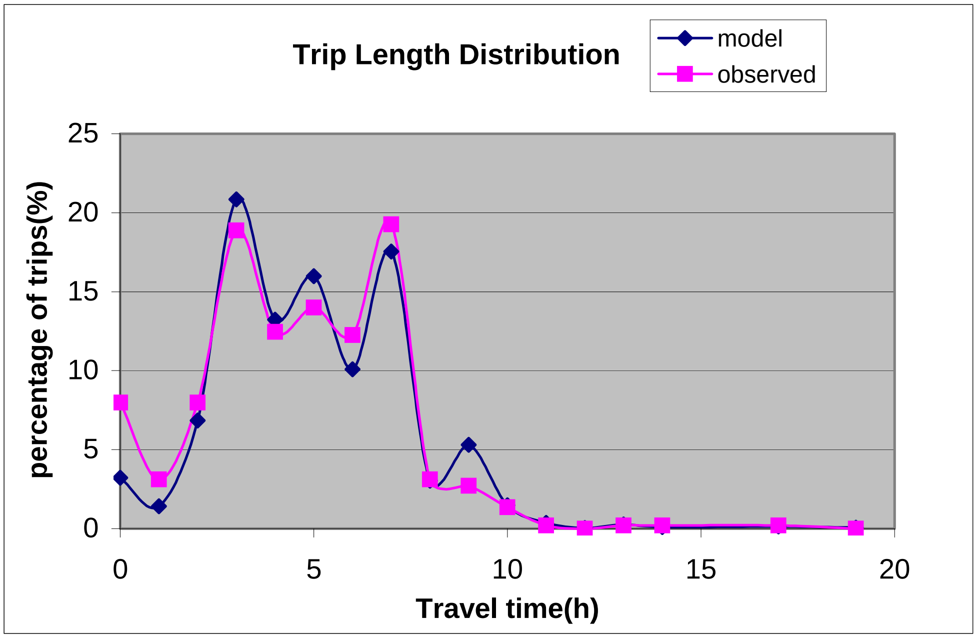


Fig.4-6 Trip length distribution of population model

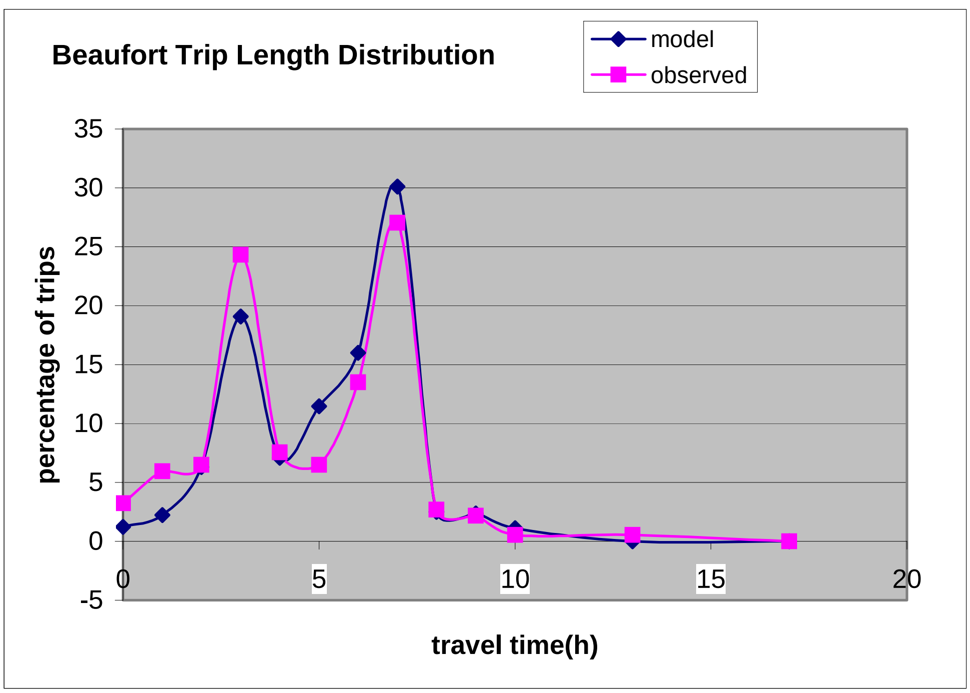


Fig.4-7 Trip length distribution, origin of Beaufort

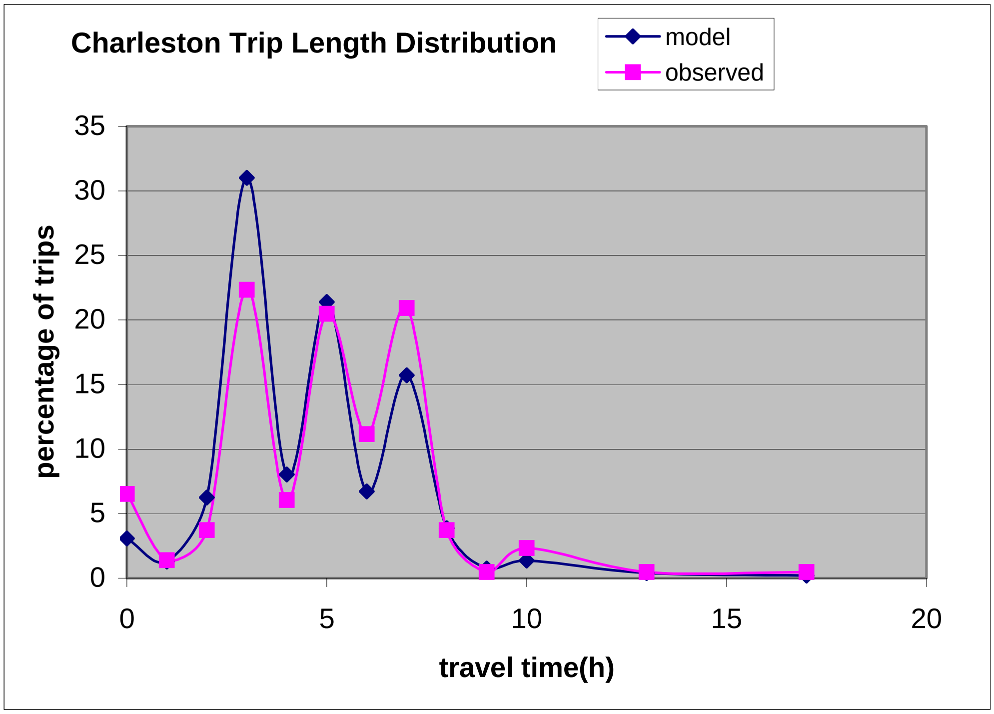


Fig.4-8 Trip length distribution, origin of Charleston

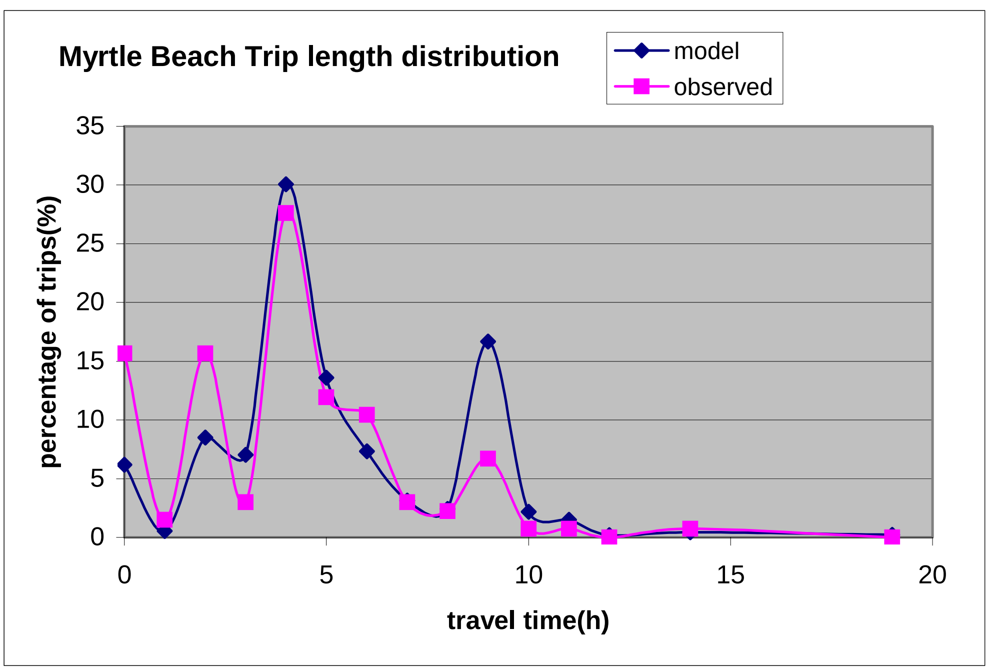


Fig.4-9 Trip length distribution, origin of Myrtle Beach

b) Hotel model:

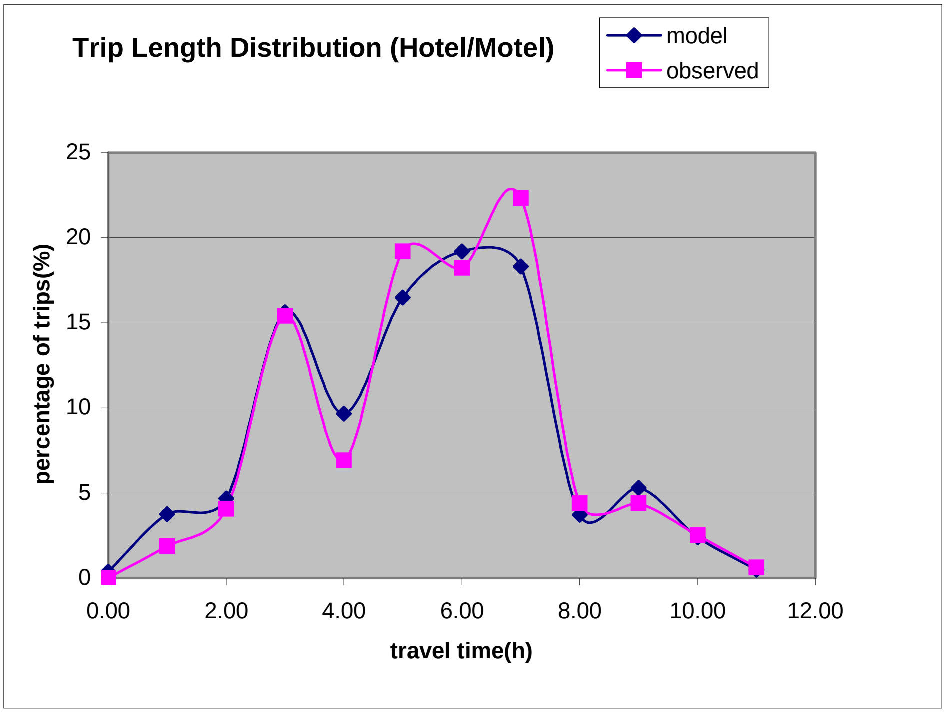


Fig.4-10 Trip length distribution of hotel model

CHAPTER 5. THEORETICAL EXTENSION OF THE INTERVENING OPPORTUNITY MODEL

5.1. Background

Apart from the distance from the origin and opportunities available in the destinations, there is another important factor that will influence the choice of destination, i.e. the path of the hurricane. Hurricanes move and change with time, but the track can be estimated roughly, so this factor can be incorporated into the intervening opportunity theory so as to better model and represent the process of hurricane evacuation.

In the seminal work of Stouffer (Stouffer 1940), he calculated the intervening opportunities by concentric circles, with the center of the circles at the origin and the intervals between the circles constant. See figure 5-1.

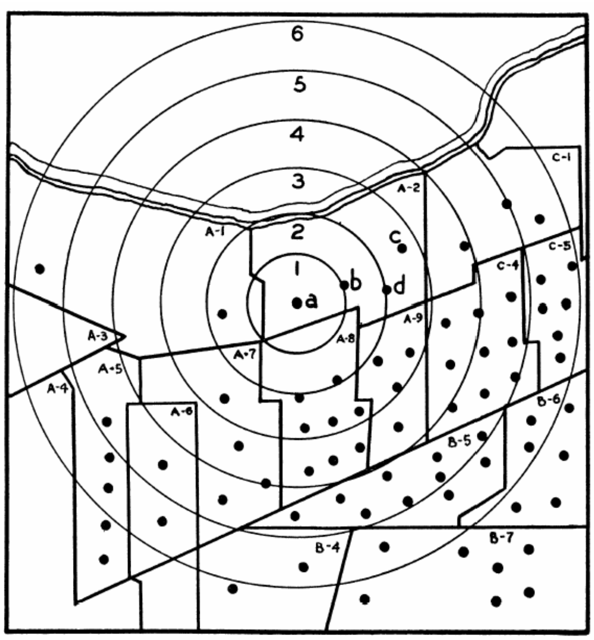


Fig.5-1 Stouffer's model
The dots in the map represent the opportunities available in their areas.

5.2 A New Extended Opportunity Model

The intervening opportunity model is a trip distribution method quite similar to the gravity model. However, unlike gravity model, which considers all the destinations simultaneously while taking into account of the travel impedance, the opportunity model considers each destination sequentially with no direct use of the impedance. The common point of these two models is that they both determine the probability of a destination being accepted, but they are based on different theoretical rationale.

The gravity model is based on an analogy with Newton's gravitational law. The possibility of choosing a destination is inversely proportional to the travel impedance. While the opportunity model is based on the assumption that the trip makers consider the destination sequentially, and each destination, if considered, will have the same probability of being accepted.

Here what is important is the sequence that the opportunity model uses for the destinations. Generally, the destinations are ordered in the sequence based on their travel impedance. This impedance is generally taken as travel distance or travel time from the origin to the destinations. Just as in Stouffer's model, a travel time contour is usually used. See Fig 5-2. The contour is a series of concentric circles where the trip maker's origin is at the center of the circles.

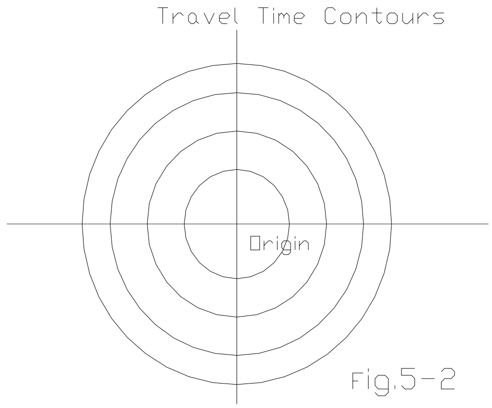


Fig.5-2 Travel time contours as concentric circles

Now what if a hurricane comes? The traveler's decision of choosing destinations will be drastically changed. Not only will he consider the travel impedance of the destinations, but also more importantly the direction he should travel to get away from the path of the hurricane. So the notion of direction in the model needs to be added, to take into consideration a "good" direction and a "bad" direction. The "bad" direction is considered to be along the path of the danger (such as the projected path of a hurricane, the wind direction for a chemical spill or fire, etc.). The impedance in that direction is artificially increased, i.e. the original impedance is factored according to the angle between the direction of the danger and the direction of the trips made. Intuitively, under these conditions the contour line of equal impedances would look like a series ellipses instead of circles, as shown in Fig.5-3.

Destinations right on the path of the danger are highly undesirable. No one would want to evacuate to a destination that a hurricane will pass. To better represent this condition, the concept of "proximity" was added, in which destinations close to

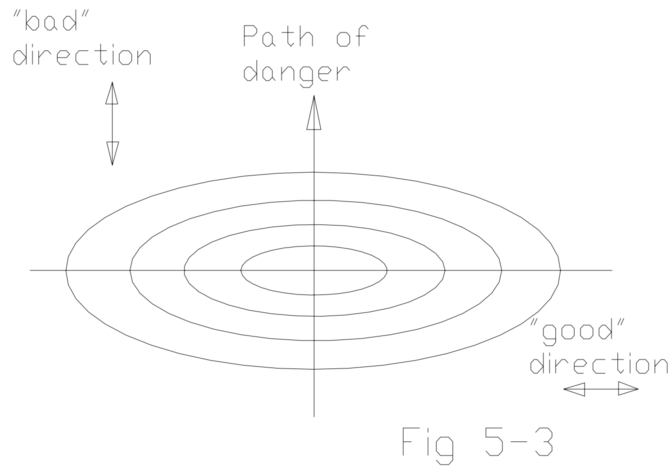


Fig.5-3 The effect of path of danger on contour lines, contours of equal destination attractiveness

the source of danger are considered unattractive, and the unattractiveness is reflected as increased travel impedance. With this approach, the contours of travel impedance are more appropriately described as contours of equal destination attractiveness. The contours then form a pattern like a bowtie, as shown in Fig.5-4.

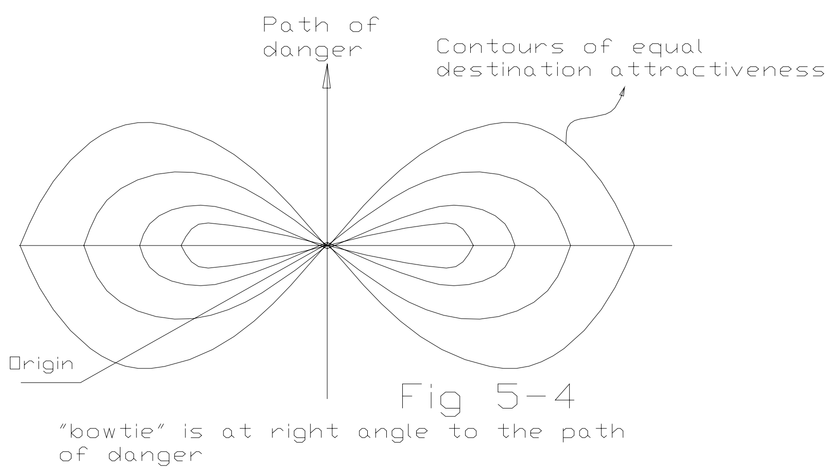


Fig.5-4 Contours of equal destination attractiveness in bowtie shape

When an origin is close to the coastline, it is intuitively expected that the axes of the bowtie need to be changed from 90° to the path, to something else to reflect the desire to flee inland and away from high winds and more flooding. See Fig.5-5

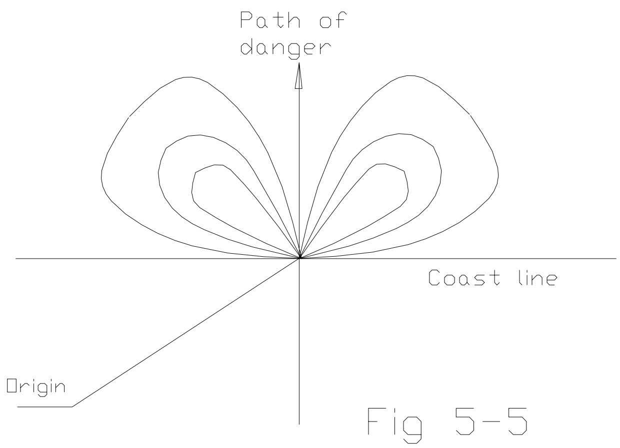


Fig.5-5 The effect of coastline on the contours

Similarly, when an origin is not on the path of the danger, the contours of equal attractiveness can reasonably expected to be asymmetrical, as shown in Fig.5-6

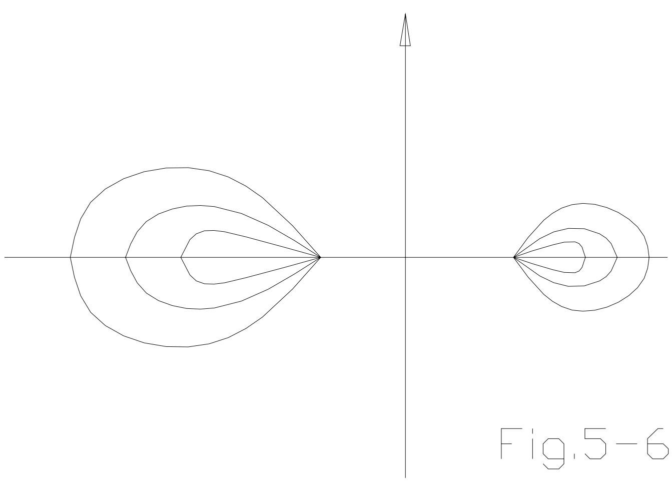


Fig.5-6 Asymmetrical contours of equal destination attractiveness

Using these assumptions, destinations can be ordered according to their new impedance or attractiveness. The intervening opportunity method can then be applied on the modified model as explained below.

5.3 Applying the Extended Opportunity Model in TransCAD

5.3.1 Introduction

An intervening opportunity model was successfully built and calibrated with Floyd data. Then an extended model based on the assumptions described in the previous section was built to incorporate the effect of the path of the hurricane on trip distribution.

5.3.2 Assumptions of the Coordinate System

The core of the data preparation process lies in the construction of "contours of equal destination attractiveness". To do this, a Cartesian coordinate system for each evacuation origin was built, and a linear transformation was applied to rotate the axes according to the direction of the hurricane. To simplify the process three basic assumptions were made:

1) The path of the hurricane in the model is a straight line.

The actual path of the hurricane is a complicated curve and cannot be forecast accurately during hurricane evacuation. However the path of a hurricane near one specific origin can be assumed to be approximated by a straight line. A more sophisticated model may be built if we have the available software and computation capability. This assumption is regarded as a justifiable and reasonable approximation.

From the National Hurricane Center, the detailed track information for Hurricane Floyd was found. See Appendix C.

With this data, the path of Hurricane Floyd can be plotted in TransCAD.

2) A Cartesian coordinate system was used that does not take into account the spherical curvature of the earth.

The earth is obviously not a flat surface but a globe. This presents a difficulty when measuring the distance between two points and mapping a large area. The "Haversine Formula" is often used to calculate the distance between two points on the surface of the earth. To demonstrate this, suppose two points 1 and 2 and their longitudes and latitudes are known, the surface distance between point 1 and point 2 may be calculated as:

$$dlon = lon_2 - lon_1$$

$$dlat = lat_2 - lat_1$$

$$a = \sin^2(\frac{dlat}{2}) + \cos(lat_1)\cos(lat_2)\sin^2(\frac{dlon}{2})$$

$$c = 2\arcsin(\min(1, \sqrt{a}))$$

$$d = R * c$$

Where R= the radius of the earth = 6367km = 3956mile

To draw the earth on a flat map, different projections and coordinate systems are used. TransCAD accommodates several coordinate systems, including:

- NAD 27: State plane and other 1927 North American Datum coordinate systems, a series of 170 coordinate systems or zones.
- NAD 83: State plane and other 1983 North American Datum coordinate systems, a series of over 140 coordinate systems or zones.

- Universal Transverse Mercator (UTM): a series of 60 coordinate systems that is intended for small regions worldwide.

In each zone or a specific projection area, there is an origin and its own central meridian. The position of one point can be described using Northing (Y-coordinate), Easting (X-coordinate) and zone number.

Not a single plane coordinate system can describe the curved earth without distortion. TransCAD will always store the information of the position of points in longitudes and latitudes in the dataview, though it supports the display of the coordinates of a point in other coordinate systems.

3) For convenience of calculation, a single Cartesian coordinate system was used.

The origin of the coordinate system was set at the origin of the evacuation. From the map it was known that the region considered in the model has latitudes that range approximately from 30 to 36 degrees.

The radius of the earth was taken as uniform and equal to 3956 miles. The surface distance between two latitude lines with 1-degree difference was calculated:

$$M = \frac{2\pi R}{360} = 69.05 miles$$

The surface distance between two longitude lines with 1-degree difference is then calculated: $N = \frac{2\pi R \cos\theta}{360}$

If θ=30º N=59.79 miles

If θ=36º N=55.86 miles

If $\theta=33^{o}$ N=57.91 miles

The largest distortion was calculated approximately as:

$$\rho = \frac{59.79 - 55.86}{55.86} = 7.04\%$$

The map was changed into a plane coordinate system by the following method:

1 degree difference of longitude = 69.05 miles difference of X-coordinate

1 degree difference of latitude = 57.91 miles difference of Y-coordinate

5.3.3 Linear Transformation on the Coordinates

To rotate the x-y axis of the Cartesian coordinate system anti-clockwise by an angle of θ, the following coordinate transform formulae was used:

$$x' = x\cos\theta + y\sin\theta$$
$$y' = y\cos\theta - x\sin\theta$$

Normally the direction of the hurricane will be used to determine the value of θ. But in this specific case study of Hurricane Floyd, the path of the hurricane is nearly parallel to the coastline, and the coast regions are high-risk areas subject to storm surge and flooding. The three evacuation origins, Beaufort, Charleston and Myrtle Beach are all located on the seashore and are almost on the same line. Therefore the direction of Beaufort-Charleston was used as the new axis reflecting the “bad” direction after rotation.

5.3.4 Selection of the Shape of the Contour Lines

As stated earlier, the contour lines in the new model are expected to have a bow-tie shape. To simulate this, a beta distribution curve was selected:

The probability density function of the beta distribution is given by:

$$f(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)*\Gamma(\beta)} * x^{\alpha-1} * (1-x)^{\beta-1}$$

Where $\Gamma(\gamma) = (\gamma - 1)!$

By selecting different parameters for α and β, curves with different shapes can be obtained. By observing the pattern of destinations from a particular origin in the data used in the study, and taking the x-axis perpendicular to the path of the storm through the origin of the trips, the parameters were selected as follows:

$\alpha = 3$ and $\beta = 2$.

So $f(x) = 12x^2(1-x)$

Every point on the same contour line will have the same "impedance" or destination attractiveness. Let i represent this value. To accommodate the fact that x is limited to values between 0 and 1 and to obtain consecutive contour lines, the beta-distribution curve must be scaled by a factor for each i. To achieve this:

Let m_i=scale factor for x for the i_{th} destination attractiveness

And, n_i=scale factor for f (x) for the i_{th} destination attractiveness

Thus, the contour line function becomes:

$$\frac{f(x)}{n_i} = 12\left(\frac{x}{m_i}\right)^2 * (1 - \frac{x}{m_i})$$

If i is the distance along the scaled x axis, then since the beta distribution curve is defined on the interval of [0,1], $m_i = i$. Further, to ensure that every contour line has the same shape and is similar with each other with no intersection, we have

$n_i = k * m_i = ki$,

Where k=constant.

The new contour line functions will be:

$$\frac{f(x)}{ki} = 12\left(\frac{x}{i}\right)^2 (1-\frac{x}{i})$$

$$f(x) = \frac{12k}{i} x^2 (1-\frac{x}{i}),$$

Let $k_0 = 12k$,
Then,

$$f(x) = \frac{k_0}{i} * x^2 (1-\frac{x}{i})$$

$$\therefore i = \frac{k_0 x^2 \pm \sqrt{k_0{}^2 x^4 - 4f(x)k_0 x^3}}{2f(x)}$$

If x=x_0 unchanged, f (x) ↓ then intuitively i ↓

$$\therefore i = \frac{k_0 x^2 - \sqrt{k_0{}^2 x^4 - 4f(x)k_0 x^3}}{2f(x)} \qquad (7)$$

Where $f(x) \neq 0$

For (7) to have meaning, it must satisfy $k_0{}^2 x^4 - 4f(x)k_0 x^3 \geq 0$

i.e. $f(x) \leq \frac{k_0}{4} x$

For every point that satisfies the above condition, we have one corresponding i value. The value of i defines which contour line (x, y) is on.

5.3.5 Equal Destination Attractiveness Contour

The i value for any specific origin and destination was calculated using the above formulae. The i value is inversely related to the attractiveness of a destination, meaning that low values of i reflect attractive destinations and high values of i reflect unattractive destinations. An example of the calculation is shown in Fig. 5-7. In the calculation, θ was taken as 119.92°, which was measured directly from the origin-destination map. There are destinations that don't have i value, which are indicated by a notation of #NUM in excel. The k_0 was taken as 10, in order to cover most of the destinations in the map. Larger value is possible but not without changing the shape of the contour lines.

Microsoft Excel

H1 = i

	A	B	C	D	E	F	G	H	J	K	L	M
1	**NAME**	**LONGITUDE**	**LATITUDE**	**x1**	**y1**	**xnew**	**ynew**	**i**			**Y/X**	**K$**
2	Abbeville SC	-82458915	34222788	-118.80	106.25	151.3984	49.98399	156.7569			0.330149	1.32059
3	Aiken SC	-81635093	33544413	-61.92	66.96	88.95305	20.26784	91.07781			0.227849	0.9114
4	Allendale SC	-81357881	32987646	-42.78	34.72	51.4473	19.76112	53.59157	cosa	sina	0.384104	1.53642
5	Anderson SC	-82637849	34519178	-131.16	123.41	172.4449	52.13131	177.9993	-0.499	0.867	0.302307	1.20923
6	Alamance NC	-79399369	36043937	92.46	211.71	137.4151	-185.806	163.8235			-1.35215	5.4086
7	Baldwin GA	-83249536	33068812	-173.39	39.42	120.7013	130.6621	137.7092	k0		1.082525	4.3301
8	Barnwell SC	-81435278	33265884	-48.12	50.83	68.08385	16.35432	69.80292	10		0.240209	0.96083
9	Beaufort SC	-80738394	32388094	0	0	0	0	0			0	0
10	Berrien GA	-83229656	31276004	-172.02	-64.40	30.00302	181.2789	#NUM!			6.042023	24.1681
11	Bibb GA	-83697822	32806713	-204.35	24.24	122.9879	165.0733	146.3678			1.342191	5.36876
12	Bulloch GA	-81743407	32397297	-69.40	0.53	35.09074	59.90052	44.89607			1.707018	6.82807
13	Buncombe NC	-82530265	35611214	-123.73	186.65	223.5669	14.13399	224.9985			0.06322	0.25288
14	Burke NC	-81704817	35749541	-66.73	194.66	202.0705	-39.2798	206.159			-0.19439	0.77755
15	Burke GA	-82000521	33060999	-87.15	38.97	77.27298	56.11394	83.8859			0.726178	2.90471
16	Cabarrus NC	-80551819	35386788	12.88	173.65	144.1297	-97.8231	155.5192			-0.67872	2.71486
17	Carroll GA	-85079715	33582645	-299.77	69.18	209.5603	225.38	238.8351			1.07549	4.30196
18	Chatham GA	-81136600	32010555	-27.50	-21.86	-5.2349	34.74892	#NUM!			-6.63793	26.5517
19	Clarke GA	-83367393	33951143	-181.53	90.52	169.0622	112.221	182.0789			0.663785	2.65514
20	Cobb GA	-84576639	33941324	-265.03	89.95	210.2349	184.8979	232.9327			0.879482	3.51793
21	Charleston SC	-79961064	32835406	53.67	25.90	-4.32502	-59.4619	#NUM!			13.74837	54.9935
22	Chester SC	-81159331	34692064	-29.07	133.42	130.1814	-41.3781	134.6052			-0.31785	1.2714
23	Clarendon SC	-80216364	33665852	36.05	73.99	46.1666	-68.1755	56.30854			-1.47673	5.90691
24	Clemson	-82929821	34692399	-151.32	133.44	191.2022	64.60503	198.14			0.337889	1.35155
25	Cleveland NC	-81555446	35334123	-56.42	170.60	176.0664	-36.2177	179.8453			-0.2057	0.82282
26	Craven NC	-77096467	35125638	251.48	158.53	11.96047	-297.136	#NUM!			-24.8432	99.3726
27	Cumberland NC	-78827197	35048228	131.97	154.05	67.70782	-191.287	#NUM!			-2.82518	11.3007
28	Cocke TN	-83121219	35925384	-164.53	204.84	259.7026	40.43365	263.877			0.155692	0.62277
29	Dougherty GA	-84216532	31533353	-240.17	-49.50	76.92774	232.923	#NUM!			3.027815	12.1113
30	Douglas GA	-84768024	33701574	-278.25	76.06	204.7919	203.2835	230.5571			0.992634	3.97054
31	Darlington SC	-79957784	34332393	53.90	112.59	70.72265	-102.917	85.90864			-1.45522	5.82087
32	Dillon SC	-79378870	34391377	93.88	116.01	53.73708	-139.279	#NUM!			-2.59186	10.3674
33	Dorchester SC	-80405345	33079484	23.00	40.04	23.23777	-39.9176	29.80423			-1.71779	6.87116
34	Davidson NC	-80212668	35792838	36.30	197.17	152.8309	-129.86	168.6431			-0.8497	3.3988
35	Davie NC	-80544325	35929312	13.40	205.07	171.1105	-113.949	184.3348			-0.66594	2.66375
36	Davidson TN	-86784719	36169436	-417.50	218.98	398.1854	252.7016	427.2839			0.634633	2.53853
37	Early GA	-84903853	31322896	-287.62	-61.69	90.04342	280.1519	#NUM!			3.111298	12.4452
38	Fannin GA	-84319832	34864168	-247.30	143.39	247.7205	142.8563	263.9378			0.576683	2.30673
39	Fayette GA	-84494075	33413963	-259.33	59.41	180.9124	195.1943	206.2928			1.078944	4.31578
40	Forsyth GA	-84125255	34225512	-233.86	106.40	208.9505	149.663	226.5431			0.71626	2.86504
41	Florence SC	-79702566	34024474	71.52	94.76	46.46888	-109.298	74.75349			-2.35207	9.40826
42	Forsyth NC	-80256181	36130384	33.30	216.72	171.2777	-137.01	187.7387			-0.79993	3.19971
43	Glynn GA	-81543613	31235482	-55.60	-66.75	-30.1257	81.51266	#NUM!			-2.70575	10.823

COMBINE

Ready

Fig.5-7 Calculation of destination attractiveness value i

To draw the contour line, a grid was first built; the smaller the grid, the more accurate the contour line can be constructed. The grid was created using TransCAD software. A 0.1-degree longitude by 0.1-degree latitude grid was selected in the menu. An elevation field was then created in the dataview of the grid point, and the calculated i value was entered into this field. TransCAD was then used to draw the contour lines using these "elevation" values. The contour lines with Beaufort as origin are shown in Fig. 5-8. As can be seen, there are certain areas along the coast that have no attractiveness because they are too close to the path of the storm.

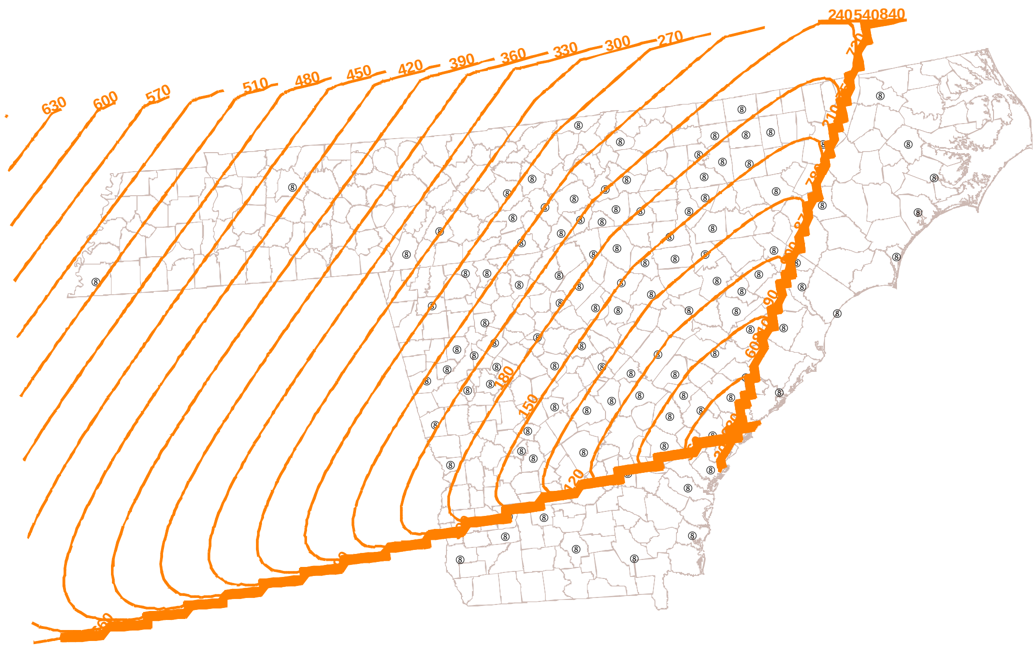


Fig.5-8 Contour lines for origin of Beaufort produced by TransCAD, k_0=10

By changing different k_0 values, the contour lines assume similar but different shapes. Fig. 5-9 shows how the contour lines would look like when we changed k_0 to 5.

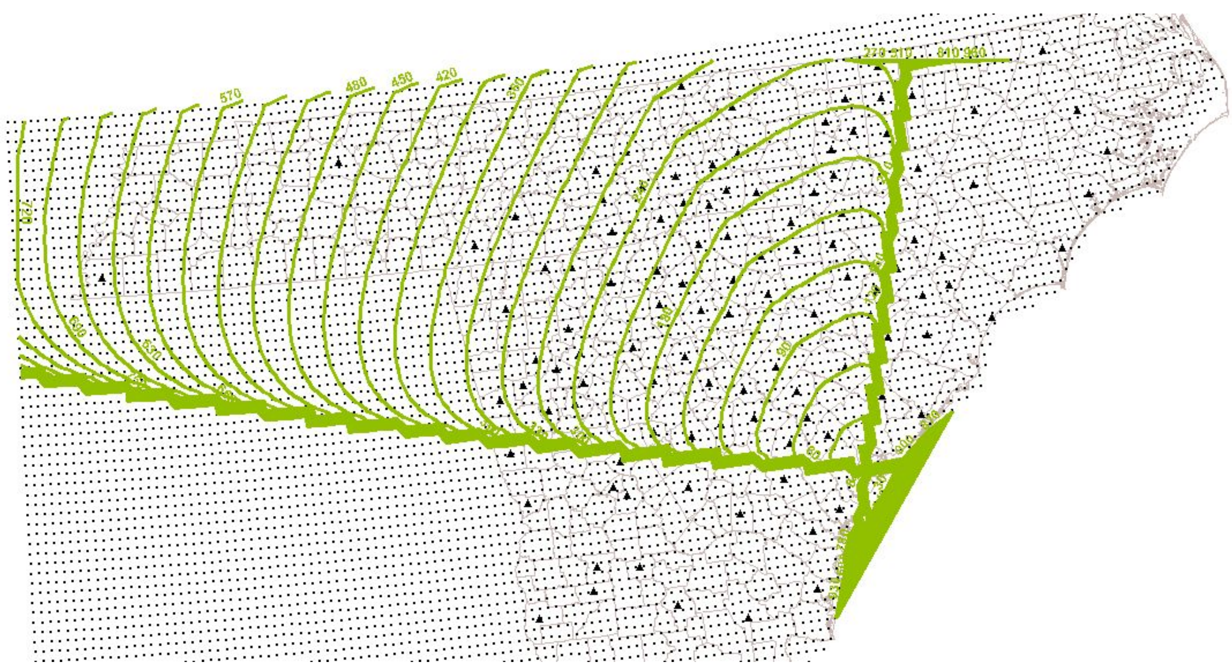


Fig.5-9 Contour lines for origin of Beaufort produced by TransCAD, k_0=5

5.3.6 Extended IOM Realization in TransCAD

The new model was applied in TransCAD to evaluate its performance. The difference between this model and original Intervening Opportunity model is only the way the destinations are ordered.

5.3.6.1 Destination Reordered Based on Attractiveness

The attractiveness of a destination was ordered using their i-value, which shows which contour line the destination is on. If the destinations are outside the region that the contour lines cover, i.e. they don't have a meaningful i-value, then they are ranked behind the destinations with i-value and ordered based on their distance to the origins.

Based on these reordered destinations, the intervening opportunities corresponding to each O-D pair was recalculated. This information was used to update the opportunity matrix that was needed in the model.

5.3.6.2 Extended IOM Calibration in TransCAD

After updating the opportunity matrix, the calibration was carried out in TransCAD. Similar to the original intervening opportunity model, the exponential forms of impedance function was selected and the opportunity matrix was used as the "impedance matrix".

For the population model, the calibration converged after 6 iterations, the calibrated L value equals to 0.0018. For the hotel model, the calibration converged after 5 iterations, the calibrated L value equals to 0.0008.

5.3.6.3 Application of the Extended IOM and Result

The application of the model was successful and the result was compared with the original intervening opportunity model and the gravity model. The detailed comparison is included in the following chapter.

CHAPTER 6. COMPARISON OF THREE DIFFERENT MODELS

6.1 Building a Gravity Model for Comparison

Another separate model on Floyd data using gravity model theory was built. The gravity model and the intervening opportunity model both belong to the category of spatial interaction models.

Friction factor table method was used to calibrate and apply the model. According to the trip length distribution characteristics of the surveyed data, the number of friction factor bins was selected to be 25. The calibration of the population model converged after 7 iterations, calibration of the hotel model converged after 1 iteration. The friction factor tables are shown in Appendix F.

6.2 Comparison of the Result of the Three Models

The performance of the three models: intervening opportunity model (IOM), Gravity Model and the extended intervening opportunity model (extended IOM) are compared using standard statistics. The statistics used for comparison are average trip length, coincidence ratio, RMSE, SRMSE (Standard Root Mean Square Error) and information gain.

6.2.1 Average Trip Length

According to the report of TMIP (Travel Model Improvement Program) of USDOT, the most standard validation check of trip distribution models are comparisons of observed and estimated trip lengths. Modeled average trip lengths should generally be within five percent of observed average trip length.

In the comparison of trip length, a uniform travel speed of 40mph over the network was assumed. The average trip length in hours is shown in table 6-1.

Table 6-1. Comparison of average trip length

	Average Trip Length in Hours / Error (%)						
	Surveyed Data	IOM		Gravity Model		IOM extended	
Population model	4.90	4.76	2.86%	4.87	0.61%	4.79	2.24%
Hotel model	5.24	5.45	4.01%	5.26	0.38%	5.22	0.38%

The gravity model produces average trip length much closer to those from the survey data than the other models. And the extended IOM shows much improvement over the IOM in this respect.

6.2.2 Coincidence Ratio

The result of different models is shown in table 6-2. The trip length distribution is aggregated using one-hour interval.

Table 6-2. Comparison of coincidence ratio

	Coincidence Ratio		
	IOM	Gravity Model	IOM extended
Population Model	0.825	0.882	0.897
Hotel Model	0.858	0.859	0.853

The performance of different models to replicate the trip length distribution is rated and ordered. For the friends/relative type of evacuation destinations, IOM extended > Gravity Model > IOM. For hotel/motel model, Gravity Model > IOM > IOM extended.

6.2.3 RMSE

The root mean square errors of different models in prediction evacuation trips are compared in table 6-3:

Table 6-3. Comparison of RMSE

	RMSE		
	IOM	Gravity Model	IOM extended
Population Model	1.64	1.55	1.55
Hotel Model	1.50	1.48	1.43

The gravity model has smaller RMSE than the intervening opportunity model, but the extended intervening opportunity model has the smallest RMSE.

6.2.4 SRMSE

Root Mean Square Error is standardized and SRMSE is calculated and tabulated.

Table 6-4. Comparison of SRMSE

	SRMSE		
	IOM	Gravity Model	IOM extended
Population Model	0.0852	0.0802	0.0804
Hotel Model	0.1377	0.1356	0.1309

The population model is better than the hotel model and has smaller SRMSE. Gravity model is better than the intervening opportunity model but not as good as the extended IOM.

6.2.5 Information Gain

The smaller the information gain, the better performance the model will have.

Table 6-5. Comparison of information gain

	Information Gain		
	IOM	Gravity Model	IOM extended
Population Model	198	177	169
Hotel Model	118	116	109

Table 6-5 shows the information gain result for the three models. The gravity model has a smaller information gain value than the intervening opportunity model. The extended IOM has an even smaller information gain value.

All the results were summarized into Table 6-6. The model with the best

Table 6-6. Summary of results of comparisons

Item		IOM	GM	Extended IOM
Average Trip Length (Error)	Population model	2.86%	**0.61%**	2.24%
	Hotel model	4.01%	**0.38%**	**0.38%**
Coincidence Ratio	Population model	0.825	0.882	**0.897**
	Hotel model	0.858	**0.859**	0.853
RMSE	Population model	1.64	**1.55**	**1.55**
	Hotel model	1.50	1.48	**1.43**
SRMSE	Population model	0.0852	**0.0802**	0.0804
	Hotel model	0.1377	0.1356	**0.1309**
Information Gain	Population model	198	177	**169**
	Hotel model	118	116	**109**

performance in each item was denoted with bold style.

6.3 Conclusion and Model Comparison

The above evaluation statistics is generally consistent and the result is quite clear. Almost all statistics show that gravity model performs better than the intervening opportunity model, and the extended intervening opportunity model better than the gravity model.

Intervening opportunity model's weakness is that it can't reflect the change in the roadway infrastructure. In the calibration and application of the intervening opportunity model, the highway network is only implicitly used as in ranking different destinations with their impedances. In other words, it's not sensitive to the change of roadway condition; for example, the evacuation contra flow measure or the designated evacuation routes will literally have no effect on this model.

As stated earlier, gravity model also has its weaknesses, especially in its incapability of reflecting the behavior of the evacuees, who will not place as much importance on the travel impedance as in an urban transportation setting, but rather will consider other factors such as the direction of the hurricane and the availability of hotels or shelters. Another weakness of the gravity model lies in its use of K-factor and its difficulty to predict future trips when social and economic characteristics change. While in the intervening opportunity model, future development, e.g. population growth or the future increase of the number of hotel establishments will be directly incorporated.

So it seems the ideal model would be some sort of combination of these two models, which may introduce an idea of " generalized impedance", the generalized impedance will not only include the travel difficulty but also the attractiveness of the destinations as well. Research has already been carried out, and the future of this kind of hybrid model is promising.

CHAPTER 7. SUMMARY AND FUTURE WORK

7.1 Summary of Model Development

Estimation of the trip distribution pattern is a critical step in evacuation planning; it is also a challenging and interesting subject. So far, few studies have addressed the issue of trip distribution under hurricane evacuation setting.

This study presents a methodology to apply intervening opportunity theory in TransCAD. This is relatively easy to implement and can be incorporated into future planning software packages.

Also we extended the intervening opportunity model to incorporate the effect of the path of the hurricane on trip distribution pattern. This produces an interesting result. Though the performance of the new model is far from satisfactory, and its implementation too complicated for practitioners, and does not possess a strong theoretical basis, there is still large room for improvement. The concept of "equal destination attractiveness contour" is fascinating. It can provide another perspective on the concept of the intervening opportunity model.

7.2 Summary of Results and Discussion

Through this experiment, we know that intervening opportunity model can be successfully applied in trip distribution using TransCAD, with some modification. The intervening opportunity model has a reasonably good performance but does not show better performance compared with the gravity model. But this is partly due to the fact that we apply the model on the same data sets that are used in calibration. In the gravity model, a friction factor method is applied; this friction factor is arbitrary and is based on empirical data. There is still question on its transferability, will the friction factors obtained from one hurricane applicable to another hurricane? Will different hurricane evacuations follow similar trip length distribution pattern? In comparison, intervening opportunity model has a better conceptual basis and focuses on the behavior aspect of hurricane evacuation, which is more attractive and has a more solid basis.

The extended intervening opportunity model performs better than the original opportunity model and the gravity model. It is a further attempt to model the behavior of the people during hurricane evacuation. This shows the strong adaptability of the intervening opportunity model and its ability to model hurricane evacuation.

Intervening opportunity model, though more complicated than gravity model and is not familiar to most practitioners, can add to the toolbox of transportation planning engineers and researchers. It can be applied in normal urban transportation setting, and can deal with many other transportation problems under special circumstances (such as emergency evacuation) as well.

7.3 Opportunities for Future Research

Intervening opportunity model has a lot of potential and holds promising research and application prospect. Some of the future researches are suggested:

1) Write program and standardize the process of applying intervening opportunity model in TransCAD.

2) Build a hybrid gravitational-opportunity model for trip distribution analysis in hurricane evacuation or for other transportation planning purposes. Discrete choice models that have an inherent basis in human behavior can also be a viable alternative.

3) Evaluate the performance of the intervening opportunity model using other hurricane survey data.

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APPENDIX A. INFORMATION ABOUT THE NODES IN THE MODELS

Nodes for the population model:

GOERGIA	SOUTH CAROLINA	NORTH CAROLINA	TENNESSEE
Atlanta	Abbeville SC	Alamance NC	Cocke TN
Baldwin GA	Aiken SC	Buncombe NC	Davidson TN
Berrien GA	Allendale SC	Burke NC	Hamilton TN
Bibb GA	Anderson SC	Cabarrus NC	McMinn TN
Bulloch GA	Barnwell SC	Cleveland NC	Sevier TN
Burke GA	Beaufort SC	Craven NC	Shelby TN
Carroll GA	Charleston SC	Cumberland NC	Sullivan TN
Chatham GA	Chester SC	Davidson NC	
Clark GA	Clarendon SC	Davie NC	
Cobb GA	**Clemson**	Forsyth NC	
Dougherty GA	Colleton SC	Guilford NC	
Douglas GA	**Columbia**	Halifax NC	
Early GA	Darlington SC	Haywood NC	
Fannin GA	Dillon SC	Henderson NC	
Fayette GA	Dorchester SC	Macon NC	
Forsyth GA	Florence SC	Mcdowell NC	
Glynn GA	Greenville SC	Mecklenburg NC	
Gordon GA	Greenwood SC	Moore NC	
Greene GA	Hampton SC	New Hanover NC	
Gwinnett GA	Jasper SC	Onslow NC	
Habersham GA	Kershaw SC	Pitt NC	
Hart GA	Lancaster SC	Polk NC	
Henry GA	Laurens SC	Randolph NC	
Houston GA	Lee SC	Rockingham NC	
Jefferson GA	Marion SC	Rowan NC	
Laurens GA	Marlboro SC	Rutherford NC	
Lee GA	**Myrtle Beach**	Swain NC	
Liberty GA	Newberry SC	Transylvania NC	
McDuffie GA	Orangeburg SC	Union NC	
Muscogee GA	Spartanburg SC	Wake NC	
Peach GA	Sumter SC	Watauga NC	
Richmond GA	Union SC		
Rockdale GA	Williamsburg SC		
Screven GA	York SC		
Toombs GA			

Troup GA			
Turner GA			
Union GA			
Ware GA			
Washington GA			
Wilkes GA			

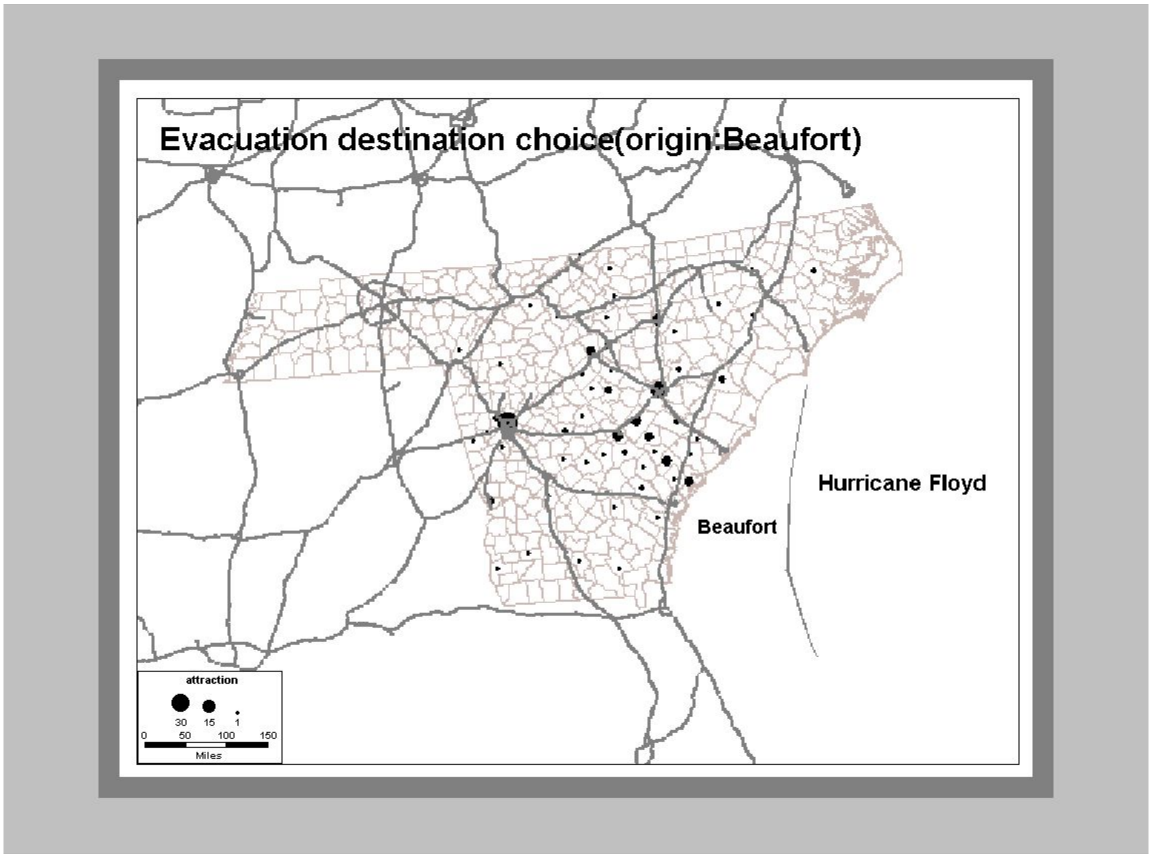
There are 113 nodes in total.

Nodes for the hotel model:

GEORGIA	SOUTH CAROLINA	NORTH CAROLINA	TENNESSEE
Atlanta	Abbeville SC	Buncombe NC	Cocke TN
Baldwin GA	Aiken SC	Burke NC	Knox TN
Bibb GA	Allendale SC	Cabarrus NC	Sevier TN
Bulloch GA	Anderson SC	Cleveland NC	
Candler GA	Barnwell SC	Durham NC	
Chatham GA	Beaufort SC	Forsyth NC	
Clark GA	Charleston SC	Guilford NC	
Cobb GA	Clemson SC	Halifax NC	
Columbus GA	Colleton SC	Hamilton NC	
Franklin GA	**Columbia**	Haywood NC	
Gordon GA	Dillon SC	Henderson NC	
Habersham GA	Florence SC	Jackson NC	
Henry GA	Greenville SC	Mecklenburg NC	
Houston GA	Greenwood SC	Moore NC	
Jackson GA	Jasper SC	Nash NC	
Jefferson GA	Kershaw SC	Pitt NC	
Laurens GA	Lancaster SC	Polk NC	
Morgan GA	Laurens SC	Robeson NC	
Newton GA	**Myrtle Beach**	Rowan NC	
Richmond GA	Newberry SC	Rutherford NC	
Rockdale GA	Orangeburg SC	Swain NC	
Spalding GA	Spartanburg SC	Wake NC	
Troup GA	Union SC		
Wilkes GA	York SC		

There are 73 nodes in total.

Evacuation Destination Choice from Origin of Beaufort:



Initial destinations (before data cleaning):

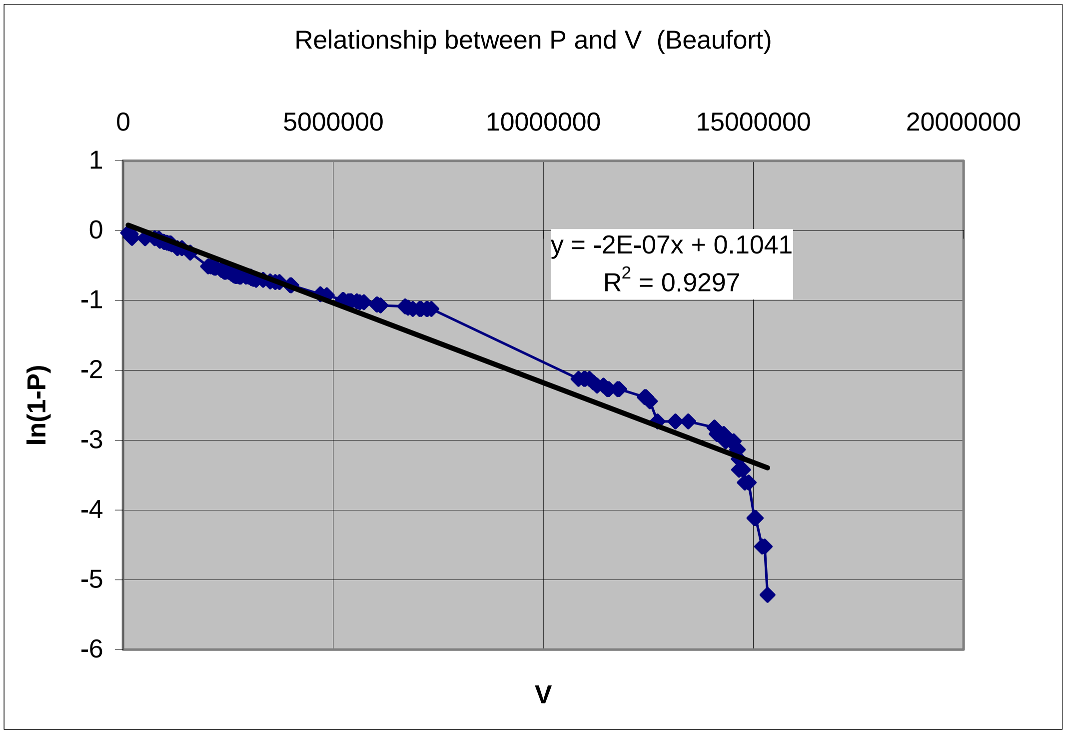
GA	SC	NC	TN
ABBEVILLE	ABBEVILLE	ASHBORO	CHATANOOGA
ACKWORTH	ABBEYVILLE	ASHBOROUGH	CHATTANOOGA
AGUSTA	ACKIN	ASHEVILLE	COLLEGEDALE
ALBANY	AIKEN	ASHVILLE	COSBY
ALPHERETTA	ALKEN	BLACK MOUNTAIN	ETOWAH
ARON	ALLENDALE	BOONE	GALLENBURG
ASHBURN	ANDERSON	BREVARD	GATENBUBG
ATHENS	ANDREWS	BUNN	GATLENBERG
ATIANTA	ARDEN	BURLINGTON	GATLINBERG
AUGUST	ASHVILLE	CANAPOLIS	GATTELINBURG
AUGUSTA	ATLANTA	CANERENK	KINGSPORT
BERIAN	AUGUSTA	CASHERES	KNOXSVILLE
BLUERIDGE	BARNWELL	CEDAR MT	KNOXVILLE
BRUNSWICK	BEACH ISALND	CHARLESTON	MAGGIE VALLEY
CALHOUN	BENNETTSVILLE	CHARLOTIE	MEMPHIS

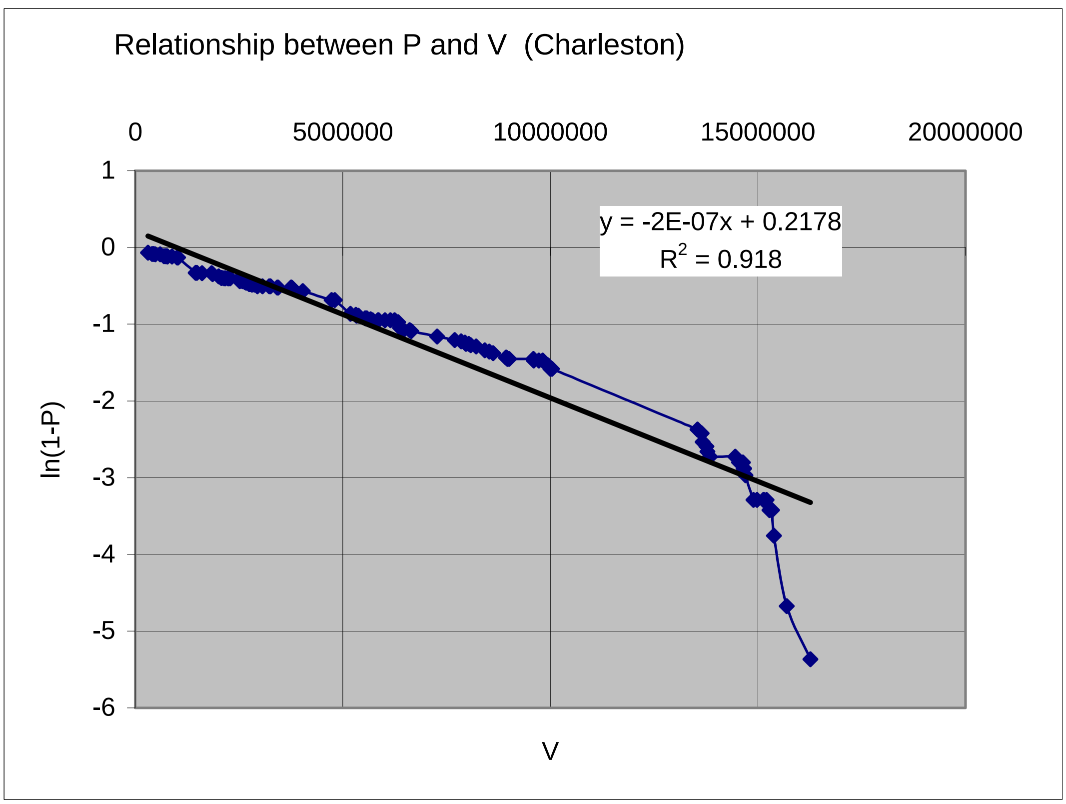
CARROLTON	BERKLEY COUNTRY AREA	CHARLOTTC	NASHVILLE
CHARLESTON	BISHOPVLLLE	CHARLOTTE	NEWPART
COLUMBUS	BLACHVILLE	CHAROLETT	NEWPORT
COMMERCE	BONVILE	CHEROKEE	PIGEON FORGE
CONWAY	BOWMAN	CHIMNEYROCK	WALDEN
CONYERS	BUXPORT	COLUMBUS	
CORNELIA	CAMDEN	CONCORD	
COVINGTON	CDLUMBIA SC	DAYETTEVILLE	
CUMMINGS	CHAFIN	FAYETTVILLE	
DECATUR	CHARLESTON	FLORANCE	
DOUGLASVILLE	CHARLOTTE	FOREST CITY	
DUBLIN	CHERROS	FRANKLIN	
DUBLINI	CHESTER	FRANKLYN	
FAYETTEVILLE	CHESTERVILLE	GREENSBORO	
FORT VALLEY	CLEMSON	GREENSWOOD	
GEORGIA	CLEVELAND	GREENVILLE	
GREENSBORO	CLINTON	GREESBORO NC	
GRIFFIN	CLLNTON	HENDERSONVILLE	
HARTWELL	COLOMBIA	HICKORY	
HELEN	COLOMBIA IRMO	HIGH POINT	
HEPHZIPHA	COLUBIA	HIGHLANDS	
HINESVILLE	COLUMBIA	HIGHPOINT	
JAKIN	COLUMBUS	JACKSONVILLE	
LAGRANGE	CONWAY	KANNAPOLIS	
LAKE THURMAN	CREMSON	LALEIGH	
LEESBURG	DARLINGTON	LEHIGH	
LOUISVILLE	DEDMONT	LINVLLLE	
LOVONIA	DILLIAN	MAGGIE VALLEY	
LYONS	DILLON	MAGGIE VALLEY NC	
MACON	DUE WEST	MAGGIEVALLEY	
MADISON	EASILY	MARION	
MARIETTA	ELLOREE	MOCKSVILLE	
MCDONOUGH	ESTILL	MONROE	
METTER	FARFAX	MORIBEL	
MILLEDGE VILLE	FAYETTVILLE	NEW BERN	
MILLIDGEVILLE	FLAGPATCH	NORTH CAROLINA	
MOUNTAIRY	FLORANCE	NORTHCAROLINA	
NEWINGTON	FLORENCE	PIGEON FORGE	
NORTHWEST	FLOURENCE	PINEHURST	
PERRY	FORTLAWN	RALEIGH	
PINE MOUNTAIN	GARDEN	RALEIGH DURHAM	
ROSWELL	GEORGETOWN	REIGHLEY	
SANDERSVILLE	GEORGIA	RIEDSVILLE	
SAVAINIA	GOOSE CREEK	RILEY	
SAVANNA	GREENSBORO	ROCKHILL	
SNELLVILLE	GREENSWOOD	ROCKINGMOUNT	
STATESBORO	GREENVILLE	ROLLAND	

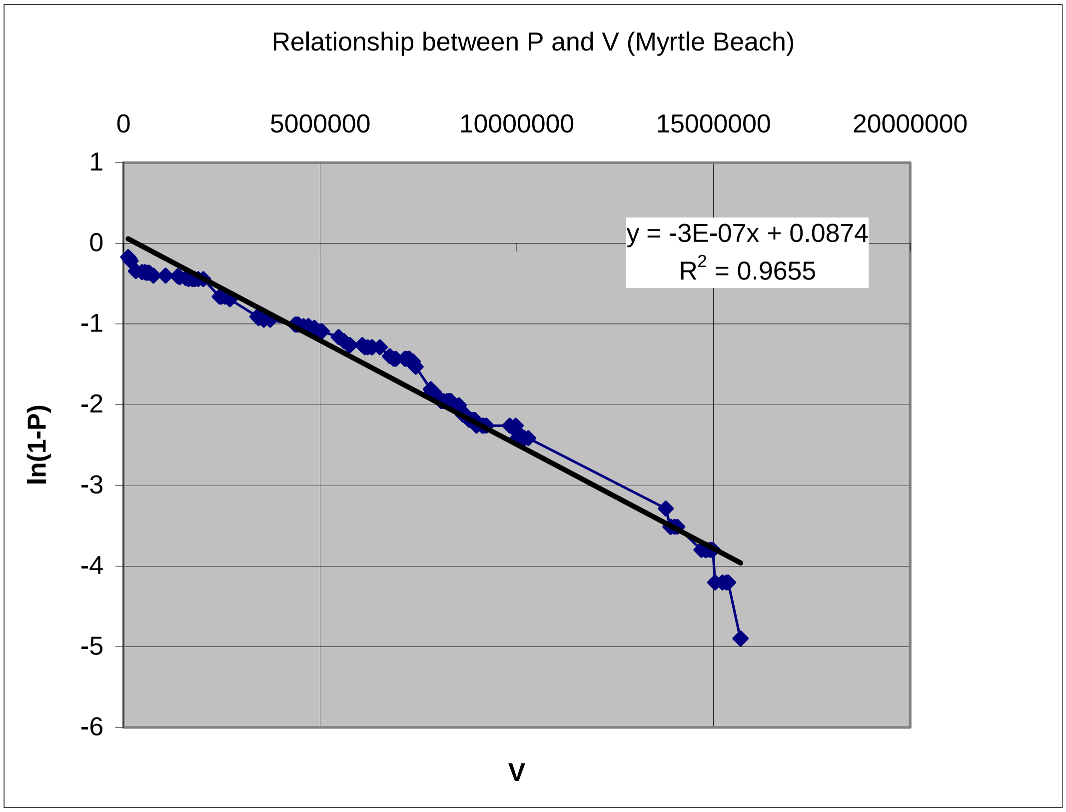
STOCKBRIDGE	GREENVILLE SC	SALISBURY	
SYLVANIA	GREENWOOD	SALUDA	
THOMPSON	GREER	SANDY REED	
TIPTON	HAMDTON	SHELBY	
WARNER ROBBINS	HAMPTON	SOMMERVILLE	
WASHINGTON	HARDEEVILLE	SOUTHERN PINES	
WASHINGTON GA	HARTSVILLE	SPINDALE	
WAYCROSS	HARTVILLE	ST MATTHEWS	
WAYNESBORO	HENDERVILLE	STATESVILLE	
YOUNGSTOWN	HILTON HEAD	THOMASVILLE	
	HOLLYWOOD	UNKNOWN MIDSTATE	
	IRMO	WAXHAW	
	JASPER	WAYNESVILLE	
	KINGSTREE	WILMINGTON	
	KINGTREE	WILSON	
	LADSON	WINSTON SALEM	
	LAKE CITY		
	LAKE CITY SC		
	LANCASTER		
	LANCASTER COUNTY		
	LATSON		
	LATTA		
	LAURENS		
	LAURSE		
	LAWRENCE		
	LEDSONI		
	LEESVILLE		
	LEXINGTON		
	LORIS		
	LOUISVILLE		
	LUMBPRTON		
	MANNING		
	MARION		
	MOUNTAIN REST		
	MOUNTS CORNER		
	MT PLEASANT		
	MULLINS		
	MYRTLE INLET		
	NEAR TENN BORDER		
	NEWBERRY		
	NINETYSIX		
	NORTH		
	NORTH AUGUSTA		
	NORTH CHARLESTON		
	OLAR		
	ORANERBURG		
	PARTYVILLE		

	PROSPERITY		
	RIDGELAND		
	ROCKHILL		
	ROCKHLLL		
	ROSEHILL		
	SANTEE		
	SENECA		
	SIMMERSONVILLE		
	SIMPSONVILLE		
	SPARTANBURG		
	SPARTENBERG		
	SPARTENBURG SC		
	SPARTICA		
	SPARTUNBURG		
	STATESBORO		
	SUMMERVILLE		
	SUMPTER		
	SUMTER		
	SURFSIDE BEACH		
	TIMMONSVILLE		
	UNION		
	VARNVILLE		
	WALTERBORO		
	WESTASHLEY		
	WILLIAMS		
	WILLISTON		
	WINSTON SALEM		
	WOODRUFF		
	YAMESSA		

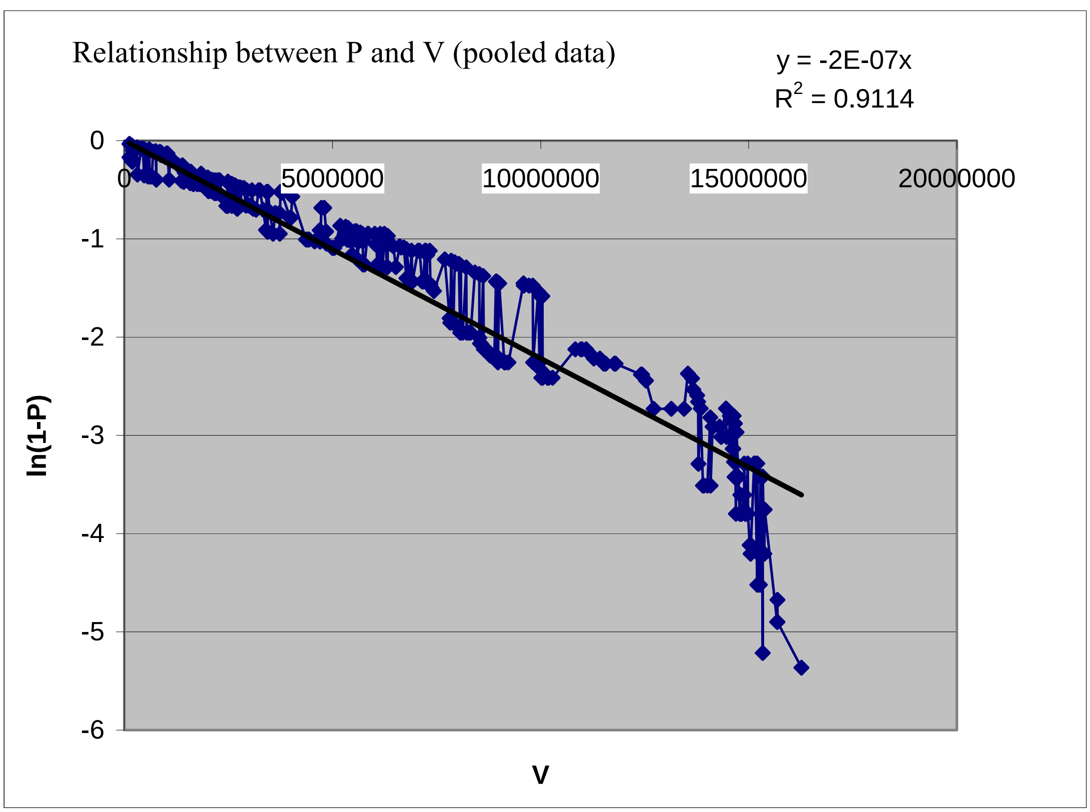
APPENDIX B. RELATIONSHIP BETWEEN P AND V FOR EACH ORIGIN, CALIBRATION OF L VALUE







Relationship between P and V (Myrtle Beach)
0
5000000
10000000
15000000
20000000
1
0
-1
-2
-3
-4
-5
-6
ln(1-P)
y = -3E-07x + 0.0874
R^2 = 0.9655
V



Relationship between P and V (pooled data)
y = -2E-07x
R^2 = 0.9114
0
-1
-2
-3
-4
-5
-6
0
5000000
10000000
15000000
20000000
ln(1-P)
V

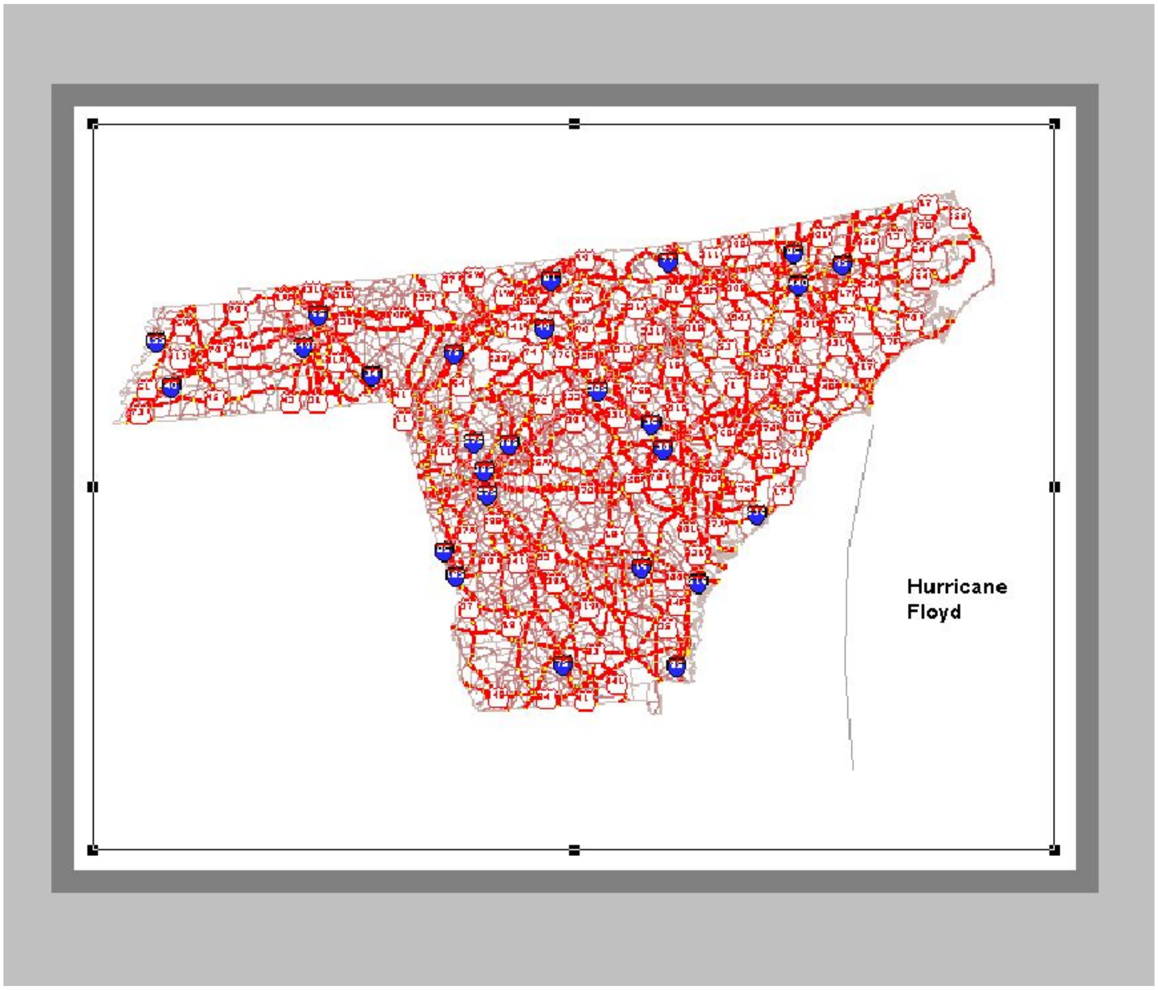
APPENDIX C. THE TRACK INFORMATION FOR HURRICANE FLOYD

ADV	TIME	LAT	LON	WIND	PRES	STATUS
1	09/07/21Z	14.6N	46.2W	30MPH	1008	T.D. 8
2	09/08/03Z	15.2N	47.5W	35MPH	1007	Tropical depression
3	09/08/09Z	15.6N	49.1W	40MPH	1005	T.S. Floyd
4	09/08/15Z	15.8N	50.0W	45MPH	1003	Tropical storm
5	09/08/21Z	16.6N	51.7W	50MPH	1000	Tropical storm
6	09/09/03Z	16.7N	53.6W	60MPH	1000	Tropical storm
7	09/09/09Z	17.3N	54.6W	60MPH	1003	Tropical storm
8	09/09/15Z	17.2N	55.5W	60MPH	1003	Tropical storm
9	09/09/21Z	18.2N	56.9W	70MPH	996	Tropical storm
9A	09/10/00Z	18.2N	57.2W	70MPH	995	Tropical storm
10	09/10/03Z	18.3N	57.7W	70MPH	995	Tropical storm
10A	09/10/06Z	18.4N	58.4W	70MPH	995	Tropical storm
11	09/10/09Z	18.9N	58.7W	70MPH	985	Tropical storm
11A	09/10/12Z	19.1N	58.9W	80MPH	989	Hurricane Floyd
12	09/10/15Z	19.3N	59.2W	80MPH	989	Hurricane
12A	09/10/18Z	19.9N	59.7W	80MPH	989	Hurricane
13	09/10/21Z	20.5N	60.0W	80MPH	975	Hurricane
13A	09/11/00Z	20.8N	60.4W	85MPH	971	Hurricane
14	09/11/03Z	21.1N	60.8W	90MPH	971	Hurricane
15	09/11/09Z	21.7N	61.6W	105MPH	963	Hurricane
16	09/11/15Z	22.2N	62.4W	110MPH	962	Hurricane
17	09/11/21Z	22.7N	63.5W	110MPH	966	Hurricane
18	09/12/03Z	22.7N	64.5W	110MPH	967	Hurricane
19	09/12/09Z	22.8N	65.9W	110MPH	960	Hurricane
19A	09/12/12Z	22.9N	66.2W	115MPH	955	Hurricane
20	09/12/15Z	23.0N	66.6W	120MPH	955	Hurricane
20A	09/12/18Z	23.2N	67.5W	120MPH	955	Hurricane
21	09/12/21Z	23.4N	68.2W	125MPH	940	Hurricane

21A 09/13/00Z 23.5N 68.7W 145MPH 932 Hurricane
22 09/13/03Z 23.6N 69.3W 145MPH 931 Hurricane
22A 09/13/06Z 23.6N 70.0W 150MPH 923 Hurricane
23 09/13/09Z 23.7N 70.6W 155MPH 922 Hurricane
23A 09/13/12Z 23.9N 71.4W 155MPH 921 Hurricane
24 09/13/15Z 24.1N 72.1W 155MPH 921 Hurricane
24A 09/13/18Z 24.2N 73.0W 155MPH 926 Hurricane
25 09/13/21Z 24.2N 73.7W 155MPH 923 Hurricane
25A 09/14/00Z 24.4N 74.1W 155MPH 924 Hurricane
26 09/14/03Z 24.5N 74.7W 155MPH 924 Hurricane
26A 09/14/06Z 24.9N 75.3W 155MPH 928 Hurricane
27 09/14/09Z 25.1N 75.9W 155MPH 927 Hurricane
27A 09/14/12Z 25.4N 76.2W 150MPH 929 Hurricane
28 09/14/15Z 25.7N 76.8W 145MPH 932 Hurricane
28A 09/14/18Z 26.0N 77.0W 140MPH 933 Hurricane
29 09/14/21Z 26.5N 77.4W 140MPH 929 Hurricane
29A 09/15/00Z 27.1N 77.6W 140MPH 934 Hurricane
30 09/15/03Z 27.7N 77.9W 140MPH 933 Hurricane
30A 09/15/06Z 28.2N 78.5W 140MPH 935 Hurricane
31 09/15/09Z 28.8N 78.8W 140MPH 938 Hurricane
31A 09/15/12Z 29.3N 78.8W 135MPH 941 Hurricane
32 09/15/15Z 29.9N 79.0W 125MPH 943 Hurricane
32A 09/15/17Z 30.3N 79.1W 125MPH 946 Hurricane
32B 09/15/19Z 30.8N 79.1W 120MPH 947 Hurricane
33 09/15/21Z 31.3N 79.0W 115MPH 949 Hurricane
33A 09/15/23Z 32.1N 78.7W 115MPH 949 Hurricane
33B 09/16/01Z 32.4N 78.6W 115MPH 950 Hurricane
34 09/16/03Z 32.9N 78.3W 115MPH 951 Hurricane
34A 09/16/05Z 33.3N 78.1W 110MPH 952 Hurricane
35A 09/16/11Z 35.2N 77.1W 100MPH 960 Hurricane
35B 09/16/13Z 36.0N 76.6W 90MPH 962 Hurricane
36 09/16/15Z 36.8N 76.0W 80MPH 967 Hurricane

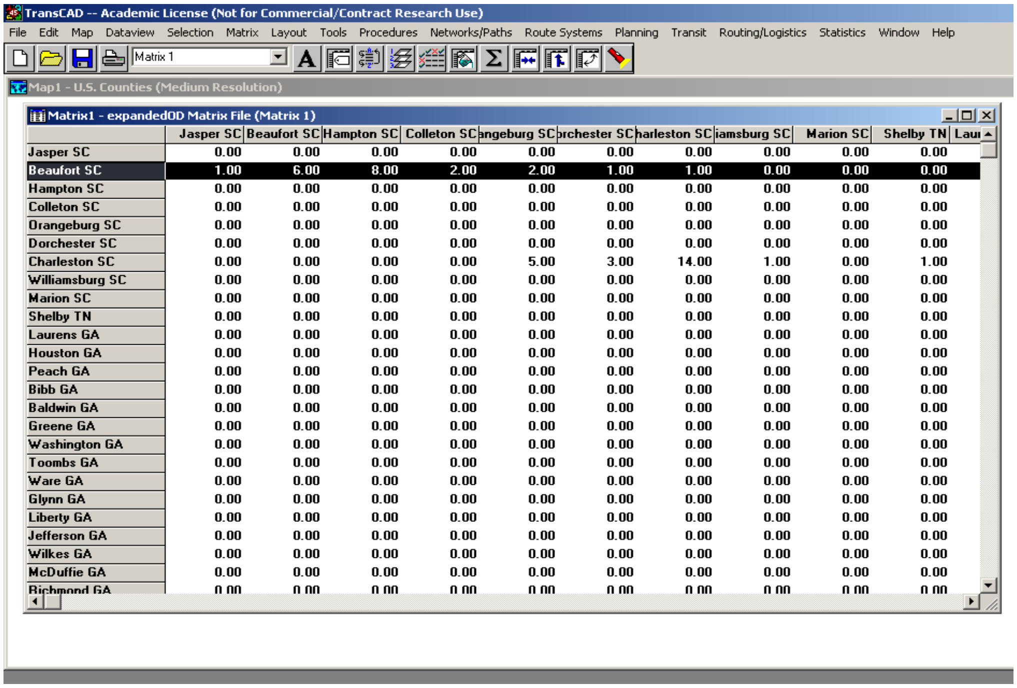
36A 09/16/18Z 37.8N 75.2W 75MPH 974 Hurricane
37 09/16/21Z 39.3N 74.6W 65MPH 974 Tropical Storm
37A 09/17/00Z 40.6N 73.5W 65MPH 974 Tropical Storm
38 09/18/03Z 41.7N 72.2W 60MPH 980 Tropical Storm
38A 09/18/06Z 42.6N 71.8W 60MPH 984 Tropical Storm
39 09/18/09Z 43.5N 70.8W 60MPH 984 Extratropical

Path of the hurricane plotted and the highway network in the TransCAD:


Hurricane
Floyd

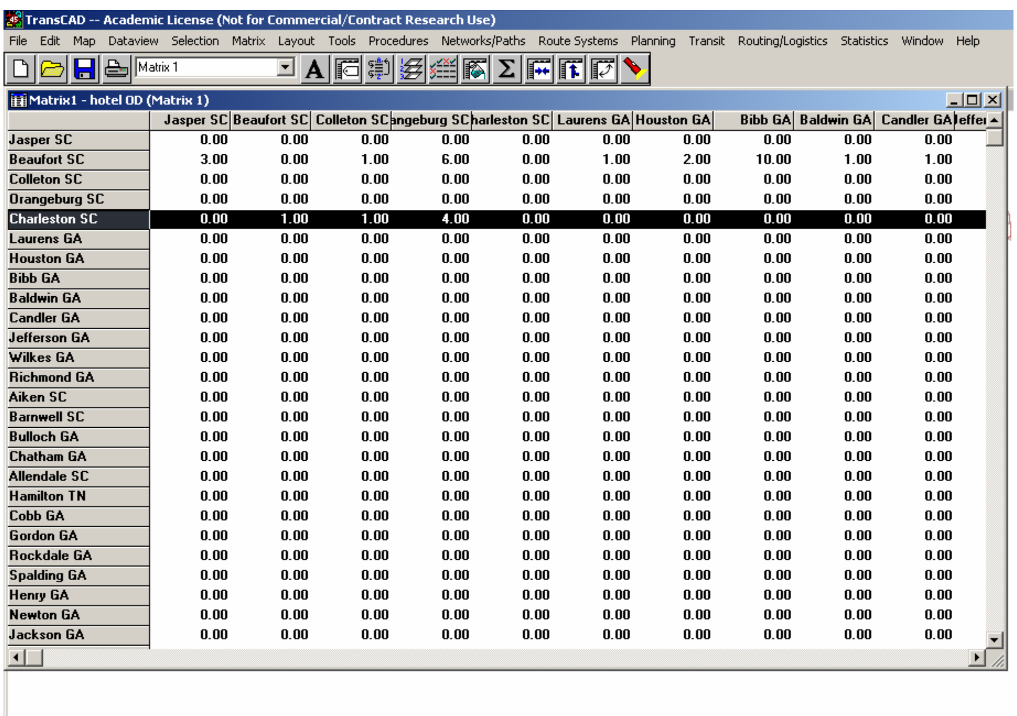
APPENDIX D. O-D MATRICES USED IN THE TWO MODELS:

1) *O-D* matrix for population model:



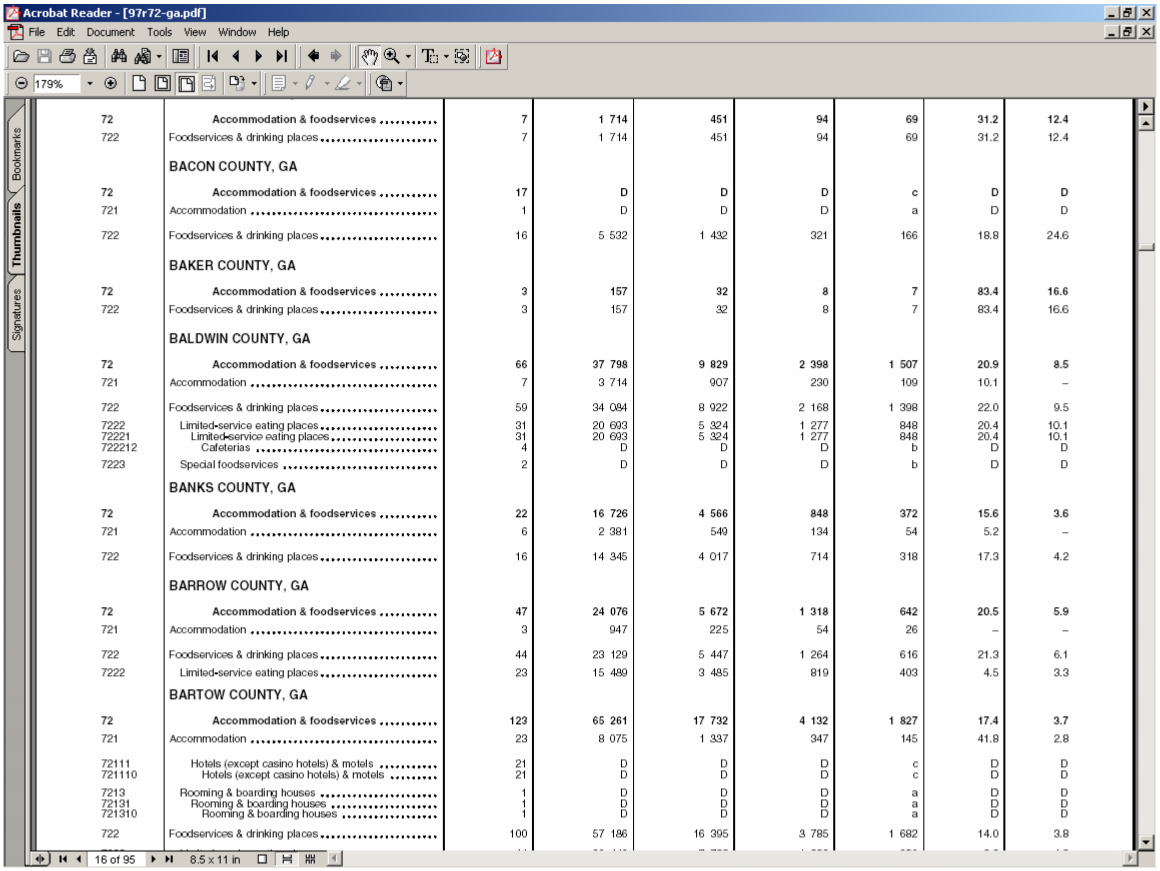
	Jasper SC	Beaufort SC	Hampton SC	Colleton SC	angeburg SC	orchester SC	harleston SC	iamsburg SC	Marion SC	Shelby TN	Laur
Jasper SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Beaufort SC	1.00	6.00	8.00	2.00	2.00	1.00	1.00	0.00	0.00	0.00	
Hampton SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Colleton SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Orangeburg SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Dorchester SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Charleston SC	0.00	0.00	0.00	0.00	5.00	3.00	14.00	1.00	0.00	1.00	
Williamsburg SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Marion SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Shelby TN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Laurens GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Houston GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Peach GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Bibb GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Baldwin GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Greene GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Washington GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Toombs GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Ware GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Glynn GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Liberty GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Jefferson GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Wilkes GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
McDuffie GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Richmond GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

2) *O-D* matrix for hotel model:



	Jasper SC	Beaufort SC	Colleton SC	angeburg SC	harleston SC	Laurens GA	Houston GA	Bibb GA	Baldwin GA	Candler GA	Jeffe
Jasper SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Beaufort SC	3.00	0.00	1.00	6.00	0.00	1.00	2.00	10.00	1.00	1.00	
Colleton SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Orangeburg SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Charleston SC	0.00	1.00	1.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00	
Laurens GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Houston GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Bibb GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Baldwin GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Candler GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Jefferson GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Wilkes GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Richmond GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Aiken SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Barnwell SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Bulloch GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Chatham GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Allendale SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Hamilton TN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Cobb GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Gordon GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Rockdale GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Spalding GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Henry GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Newton GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Jackson GA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

APPENDIX E. THE 1997 ECONOMIC CENSUS DATA (PART)



72	**Accommodation & foodservices**	**7**	**1 714**	**451**	**94**	**69**	**31.2**	**12.4**
722	Foodservices & drinking places	7	1 714	451	94	69	31.2	12.4
	BACON COUNTY, GA							
72	**Accommodation & foodservices**	**17**	**D**	**D**	**D**	**c**	**D**	**D**
721	Accommodation	1	D	D	D	a	D	D
722	Foodservices & drinking places	16	5 532	1 432	321	166	18.8	24.6
	BAKER COUNTY, GA							
72	**Accommodation & foodservices**	**3**	**157**	**32**	**8**	**7**	**83.4**	**16.6**
722	Foodservices & drinking places	3	157	32	8	7	83.4	16.6
	BALDWIN COUNTY, GA							
72	**Accommodation & foodservices**	**66**	**37 798**	**9 829**	**2 398**	**1 507**	**20.9**	**8.5**
721	Accommodation	7	3 714	907	230	109	10.1	–
722	Foodservices & drinking places	59	34 084	8 922	2 168	1 398	22.0	9.5
7222	Limited-service eating places	31	20 693	5 324	1 277	848	20.4	10.1
72221	Limited-service eating places	31	20 693	5 324	1 277	848	20.4	10.1
722212	Cafeterias	4	D	D	D	b	D	D
7223	Special foodservices	2	D	D	D	b	D	D
	BANKS COUNTY, GA							
72	**Accommodation & foodservices**	**22**	**16 726**	**4 566**	**848**	**372**	**15.6**	**3.6**
721	Accommodation	6	2 381	549	134	54	5.2	–
722	Foodservices & drinking places	16	14 345	4 017	714	318	17.3	4.2
	BARROW COUNTY, GA							
72	**Accommodation & foodservices**	**47**	**24 076**	**5 672**	**1 318**	**642**	**20.5**	**5.9**
721	Accommodation	3	947	225	54	26	–	–
722	Foodservices & drinking places	44	23 129	5 447	1 264	616	21.3	6.1
7222	Limited-service eating places	23	15 489	3 485	819	403	4.5	3.3
	BARTOW COUNTY, GA							
72	**Accommodation & foodservices**	**123**	**65 261**	**17 732**	**4 132**	**1 827**	**17.4**	**3.7**
721	Accommodation	23	8 075	1 337	347	145	41.8	2.8
72111	Hotels (except casino hotels) & motels	21	D	D	D	c	D	D
721110	Hotels (except casino hotels) & motels	21	D	D	D	c	D	D
7213	Rooming & boarding houses	1	D	D	D	a	D	D
72131	Rooming & boarding houses	1	D	D	D	a	D	D
721310	Rooming & boarding houses	1	D	D	D	a	D	D
722	Foodservices & drinking places	100	57 186	16 395	3 785	1 682	14.0	3.8

APPENDIX F. FRICTION FACTOR TABLES FOR POPULATION MODEL AND HOTEL MODEL

Population Model		Hotel Model	
Bins	FF	Bins	FF
0	12.884	0	0
1	1	1	1
2	1	2	1
3	1	3	1
4	1	4	1
5	1	5	1
6	1	6	1
7	1	7	1
8	1	8	1
9	1	9	1
10	1	10	1
11	1	11	1
12	1	12	1
13	1	13	1
14	1	14	1
15	1	15	1
16	1	16	1
17	1	17	1
18	1.17	18	1

19	1	19	1
20	1.17	20	1
21	1.17	21	1
22	1.17	22	1
23	1.17	23	1
24	1.17	24	1
25	1	25	1.003

VITA

Bin Chen was born on February 21, 1979, in the city of Jieyang, Guangdong Province, People's Republic of China. He obtained his Bachelor of Science degree in Civil Engineering in 2001 from Tsinghua University, Beijing, China. He worked and studied in Tsinghua University before he joined the Louisiana State University in August 2003. In May 2005, he will receive the degree of Master of Science in Civil Engineering.